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Efficient Enhancement Technique for Grape Leave Images Using Log Ratio Method

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A B S T R A C T

Grape leaf images are utilized for prediction of any disease present in the grape plant. The accurate and early detection of disease or any abnormality is crucial for effective treatment and improved yield outcomes. It is evident that the performance of these systems depends heavily on the quality of input images used in enhancement. The extent of image quality the efficient image enhancement is extremely required. In this paper, an enhancement framework is proposed for grape leaf image enhancement using Niphad Grape Leaf Disease (NGLD) dataset. The proposed methodology consists of several techniques that includes median filtering (MF), Contrast Limited Adaptive Histogram Equalization (CLAHE), Intensity Adjustment (IA) and Log Ratio difference (LRD) techniques. The evaluation of proposed methodology is performed using entropy, Peak Signal to Noise Ratio (PSNR), Feature Similarity Index Metrics (FSIM), Spectral similarity Index Metrics (SRSIM), Mean Absolute Error (MAE), and Universal Quality Index (UQI). The proposed methodology outperforms state of the art methods.

Keywords: Grape leaf image, Enhancement, Log ratio difference, CLAHE

1. Introduction

Here Grapes are one of the world's most economically important horticultural crops. Grapevine cultivation underpins significant agribusiness sectors that includes wine, raisins, and juice that supports farmers livelihoods in many regions (Aher et al., 2025). Grapes are categorized as real berries since they have a fleshy pericarp throughout. Their colors can vary from deep purple to red and green. These fruits, that are part of the flowering plant genus Vitis, are produced on deciduous woody vines. However, grapevines are vulnerable to numerous diseases (fungal, bacterial, viral, and pest-related) that can dramatically reduce yield and fruit quality. Common diseases such as powdery mildew, downy mildew, and black rot not only diminish crop output but also compromise grape quality, threatening the economic returns of growers (Aher et al., 2025). Early detection of such diseases on grape leaves is therefore crucial for precision agriculture and cost-effective disease management. Historically, disease diagnosis was manual and time-consuming, but recent advances in computer vision and machine learning (ML) have enabled automated leaf-based diagnosis with high accuracy. Automated systems process leaf images to extract discriminative features and classify disease presence or grape variety. This literature review examines image pre-processing (using CLAHE), used for grape leaf tasks like enhancement in peer-reviewed studies (Aher et al., 2025).

1.1 Types of Abnormalities in Grape Leaf

The abnormalities or diseases present in a grape leaf image can be there due to 4 reasons. Some of these grape diseases like fungi, bacteria, viruses and pests.

Powdery Mildew (Uncinula necator) is one of the common fungal disease identified by a white, powdery growth that is seen on grape plant leaves, stems, and fruit clusters (Sanghavi et al., 2021). Downy Mildew (Plasmopara viticola), causes yellowish patches on the top surface of grape plant leaves together with a matching downy development on the under surface (Koledenkova et al., 2022). Botrytis cinerea (Botrytis Bunch Rot) also referred to as gray mold, this disease causes grape bunches to rot and shrink. Black Rot (Guignardia bidwellii) is a fungus that develops circular, black patches on grape plant leaves and fruit, which eventually leads to early defoliation and loss of yield. Phomopsis viticola and Phomopsis Cane is a fungal disease that causes tiny reddish-brown patches to appear on the leaves and canes of grape plants, which eventually results in defoliation and decreased vine vigor (Úrbez-Torres et al., 2013). Grape plant leaves and fruit develop uneven, sunken lesions due to anthracnose (Elsinoë ampelina), which is also a fungal infection that eventually causes fruit degradation. Pierce's Disease (Xylella fastidiosa) is a bacterial illness that is spread by certain insects that causes grape vines to wilt, burn their leaves, and finally die. Crown gall (Agrobacterium vitis) is also a bacterial disease that creates growths on grapevine roots and canes that resemble tumors and prevent the vines from absorbing nutrients (Kuzmanović et al., 2018). Grapevine Leaf roll Disease is a viral infection that causes grapevine leaves to roll downward and turn red, which eventually lowers the quality of the fruit (Faist et al., 2016). Leaf blight is also a widespread fungal disease that affects grapevines, grape leaf blight is also known as grape leaf spot. It starts the development of tiny spots on the leaves and is brought on by a variety of fungal infections. These patches may enlarge and turn brown or black as the illness worsens (Liu et al., 2020). The figure 1, illustrates four common types of grape diseases and their effect on grape leaves.

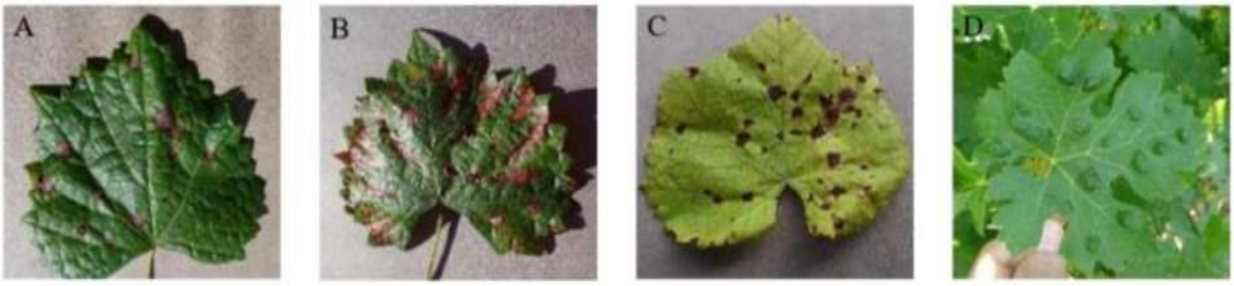


Fig. 1 Grape diseases a) Black rot b) Black measles c) Leaf blight d) Mites

The severity of these notable grape plant diseases varies depending on factors including grape type, climate, and management techniques. These are only a handful of the illnesses that may be discovered in vineyards. To maintain the health and yield of grape vines, accurate disease detection and timely treatment are essential. Some grape diseases of plants might have symptoms that are quite similar to one another, which could make it difficult to distinguish one disease from another. Complex algorithms have to be used in order to distinguish between these identical symptoms.

2. Literature Review

Image enhancement (preprocessing) aims to improve image quality (contrast, noise reduction) before feature extraction. Common approaches include filtering, histogram equalization, and normalization. Among these, Contrast Limited Adaptive Histogram Equalization (CLAHE) has become a standard tool for leaf images. CLAHE is a localized form of histogram equalization: it divides an image into contextual regions (tiles), equalizes each region's histogram with a clip limit to avoid noise amplification, and then combines the tiles. This process enhances local contrast and reveals subtle disease symptoms without excessively amplifying noise. Sai et al. (2023) note that CLAHE is used to improve contrast levels of the plant leaf image decomposing the image into tiles and clipping histograms to prevent over-amplification (Sai et al., 2023). Many grape-leaf studies explicitly apply CLAHE like Aher et al. (2025) report using CLAHE to eliminate noise, sharpen edges, and enhance contrast in grape leaf images (Aher et al., 2025). Similarly, Bajait and Malarvizhi (2024) applied CLAHE along with bilateral filtering in their preprocessing pipeline to enhance contrast before feature extraction (Bajait & Malarvizhi, 2024).

CLAHE overcomes limitations of global histogram equalization by adaptively enhancing contrast in small regions. In practice, pipelines often combine denoising filters (median, Gaussian, bilateral) with CLAHE. For example, one hybrid approach first applies bilateral filtering to remove noise while preserving edges, then applies CLAHE to locally boost contrast (Prashant G. Aher, 2025). Bajait et al. also used adaptive bilateral filtering together with CLAHE to reduce noise and improve contrast. Research has shown that CLAHE preprocessed images can significantly improve classification accuracy. Indeed, many CNN and ML based models achieve high accuracy when trained on CLAHE enhanced leaf images (Bajait & Malarvizhi, 2024). However, CLAHE has drawbacks. While it effectively enhances subtle pathological features, it can also introduce artifacts from uneven lighting and non-uniform illumination. For instance, one study notes that CLAHE can produce inconsistencies due to lighting variations, potentially harming model stability. In response, some researchers explore alternative or complementary techniques. A recent method, Mid-Point Normalization (MPN), directly scales and centers pixel intensities for neural networks, claiming more consistent inputs than CLAHE. Nevertheless, CLAHE remains widely used because it makes diseased regions more visible without needing labeled data or extensive computation. In summary, CLAHE and related adaptive histogram methods are a cornerstone of grape leaf image enhancement, typically combined with denoising filters (Taufik et al., 2025). These techniques improve contrast and highlight disease symptoms, facilitating more reliable feature extraction and classification.

After performing enhancement on grape leave images, the next step is to perform extraction of feature using numerical descriptors computing which deals with observing characteristics of leaf. Many approaches calculated the following categories of features: texture, color, shape or hybrid combinations. Texture captures are gray-level patterns like disease spots and has been extensively used. The most common are Haralick (GLCM) features, which quantify texture via statistics of the gray-level co-occurrence matrix. Typical Haralick features include contrast, correlation, energy, and homogeneity. Aher et al. (2025) explicitly extract Haralick texture features from grape leaves to distinguish disease classes (Prashant G. Aher, 2025). Image enhancement (preprocessing) aims to improve image quality (contrast, noise reduction) before feature extraction. Common approaches include filtering, histogram equalization, and normalization. Among these, Contrast Limited Adaptive Histogram Equalization (CLAHE) has become a standard tool for leaf images. CLAHE is a localized form of histogram equalization: it divides an image into contextual regions (tiles), equalizes each region's histogram with a clip limit to avoid noise amplification, and then combines the tiles. This process enhances local contrast and reveals subtle disease symptoms without excessively amplifying noise. Sai et al. (2023) note that CLAHE is used to improve contrast levels of the plant leaf image decomposing the image into tiles and clipping histograms to prevent over-amplification (Sai et al., 2023). Many grape-leaf studies explicitly apply CLAHE like Aher et al. (2025) report using CLAHE to eliminate noise, sharpen edges, and enhance contrast in grape leaf images (Aher et al., 2025). Similarly, Bajait and Malarvizhi (2024) applied CLAHE along with bilateral filtering in their preprocessing pipeline to enhance contrast before feature extraction (Bajait & Malarvizhi, 2024). CLAHE overcomes limitations of global histogram equalization by adaptively enhancing contrast in small regions. In practice, pipelines often combine denoising filters (median, Gaussian, bilateral) with CLAHE. For example, one hybrid approach first applies bilateral filtering to remove noise

while preserving edges, then applies CLAHE to locally boost contrast (Prashant G. Aher, 2025). Bajait et al. also used adaptive bilateral filtering together with CLAHE to reduce noise and improve contrast. However, CLAHE has drawbacks. While it effectively enhances subtle pathological features, it can also introduce artifacts from uneven lighting and non-uniform illumination. For instance, one study notes that CLAHE can produce inconsistencies due to lighting variations, potentially harming model stability. In this paper a hybrid methodology is applied for enhancement of diseases present in grape leave images.

3. Proposed Methodology

In the proposed methodology, proper enhancement of images is extremely required. The enhanced images can reveal subtle features or abnormalities present. By enhancing the images, agronomists and farmers can better distinguish between different types of diseases. In the proposed methodology, grape leave images are used from the Niphad grape leaf image dataset is taken, and experimentation work is carried out using Matlab 2021a software. The Niphad grape leaf dataset is a comprehensive collection grape leaf data, meticulously curated to support research and development. The dataset has 1254 normal and 1472 abnormal images captured using mobile phones for real-world authenticity. The figure 2 describes the steps involved in the enhancement.

3.1 RGB image splitting

In the initial steps, colored grape leave image image is taken and resized to 256×256 pixel size. Its red, green, blue components are divided. The operations on each component will provide much better results as compared to operations on combined images.

3.2 Median filtering

The noise present in each component is removed using the 3×3 size median filter. The unwanted characteristics present in each component will affect the efficient enhancement of images. The noise should be eliminated in initial steps (Gavhale et al., 2014).

3.3 RGB color model LAB color model conversion

The red green and blue components obtained after median filtering are merged to obtain updated RGB form of grape leave images. The updated RGB image is then converted into LAB color space model. The LAB color space model. The LAB color space is designed to approximate human vision and perception. Equal distances in the LAB color space correspond to approximately equal perceived color differences by the human eye.

3.4 ‘L’ part of LAB color model with CLAHE

The ‘L’ component denotes lightness part of LAB color model. Since the L component represents lightness, it can be used to represent grayscale images or to convert color images to grayscale while preserving the essential features. The CLAHE applied on ‘L’ segment of LAB. When applied to the L component of the LAB color model, it effectively increases the local contrast of the luminance channel without introducing unwanted color distortions or artifacts. This ensures that the original color characteristics of the image are preserved, while the contrast in the luminance channel is enhanced (Sunny & Indra Gandhi, 2018).

3.5 LAB color model RGB color model conversion

The new ‘L’ component and ‘AB’ component are combined to an extent such that new LAB color model of grape leave image. The LAB color model is converted into RGB color model. The new RGB color model of grape leave image have higher lightness as compared to previous image.

3.6 Intensity Adjustment

The updated RGB image is applied in order to perform intensity adjustment. RGB color model intensity adjustment is a straightforward and intuitive process. It involves scaling the values of all three color components by a constant factor that will increase or decrease the overall brightness of the image (Dungphonthong & Sa-ngiamvibool, 2019).

3.7 Log Ratio Difference on Green channel

The log ratio difference method is implemented on the green channel of new RGB image. The log ratio difference can amplify subtle variations in the green channel, which may be difficult to discern in the original RGB image. This can be useful for detecting and analyzing small-scale features or patterns related to its characteristics.

3.8 Enhanced Grape leave image

The green channel image obtained after the implementation of log ratio difference, is merged to obtain final RGB image. The resultant image is capable of providing sufficient features so as to perform detection of type of disease present in grape leave image.

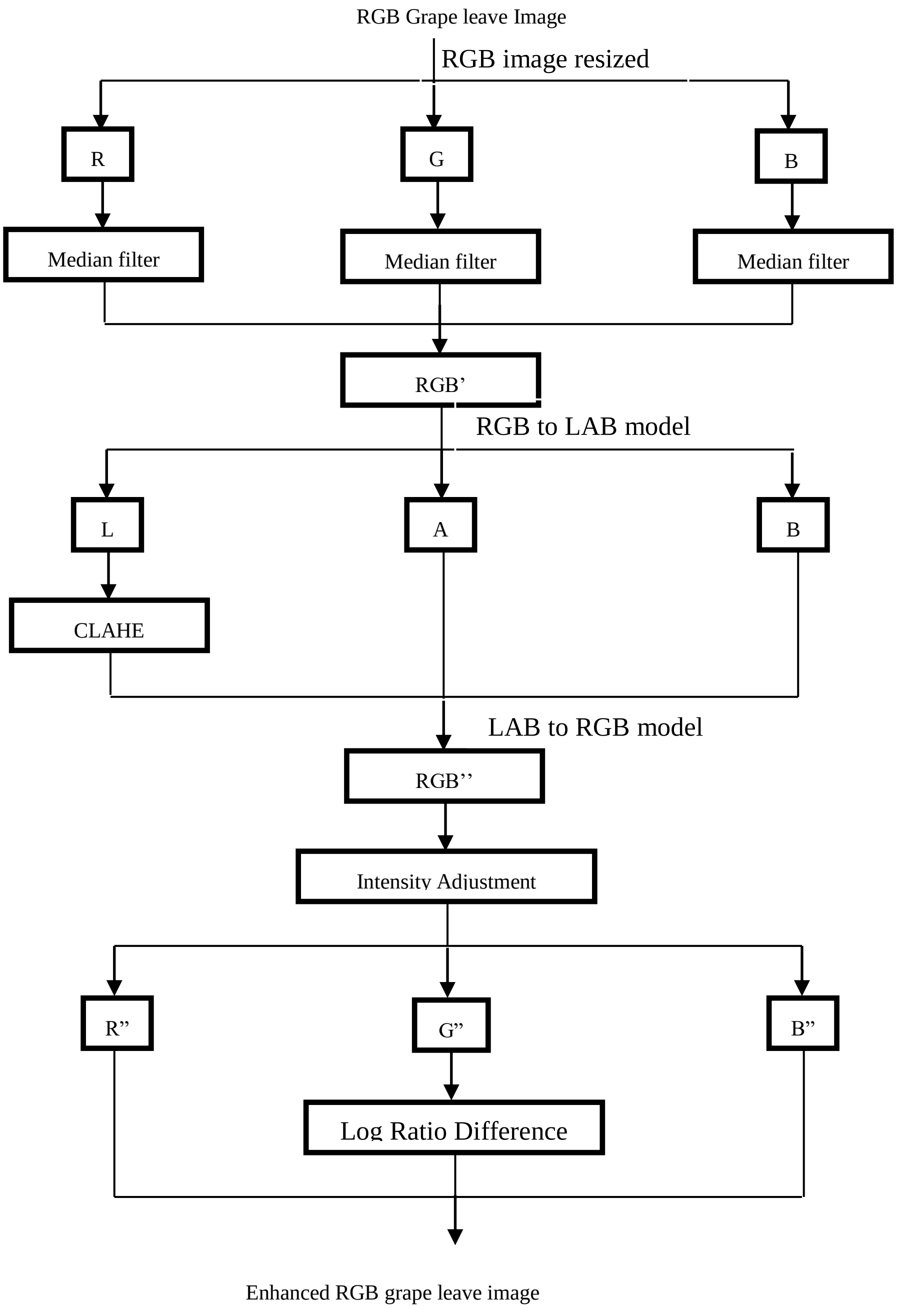


Fig.2 Proposed methodology for enhancement of grape leave images

4. Results and Discussions

In the proposed methodology for grape leave image enhancement, the dataset is used. The Niphad grape leaf image dataset is a collection of grape leave images that has been curated for the purpose of aiding in the development and evaluation of computer-aided diagnosis systems for various diseases. This dataset consists of a large number of high-quality images. The images in the Niphad grape leaf dataset are categorized according to various types of diseases. The research going on over this dataset, ensures relevant information for training and testing machine learning models. After the application of proposed methodology, some of the resultant enhanced images obtained are represented in fig. 3, the commonly used methods applied by researchers were also shown for comparative analysis.

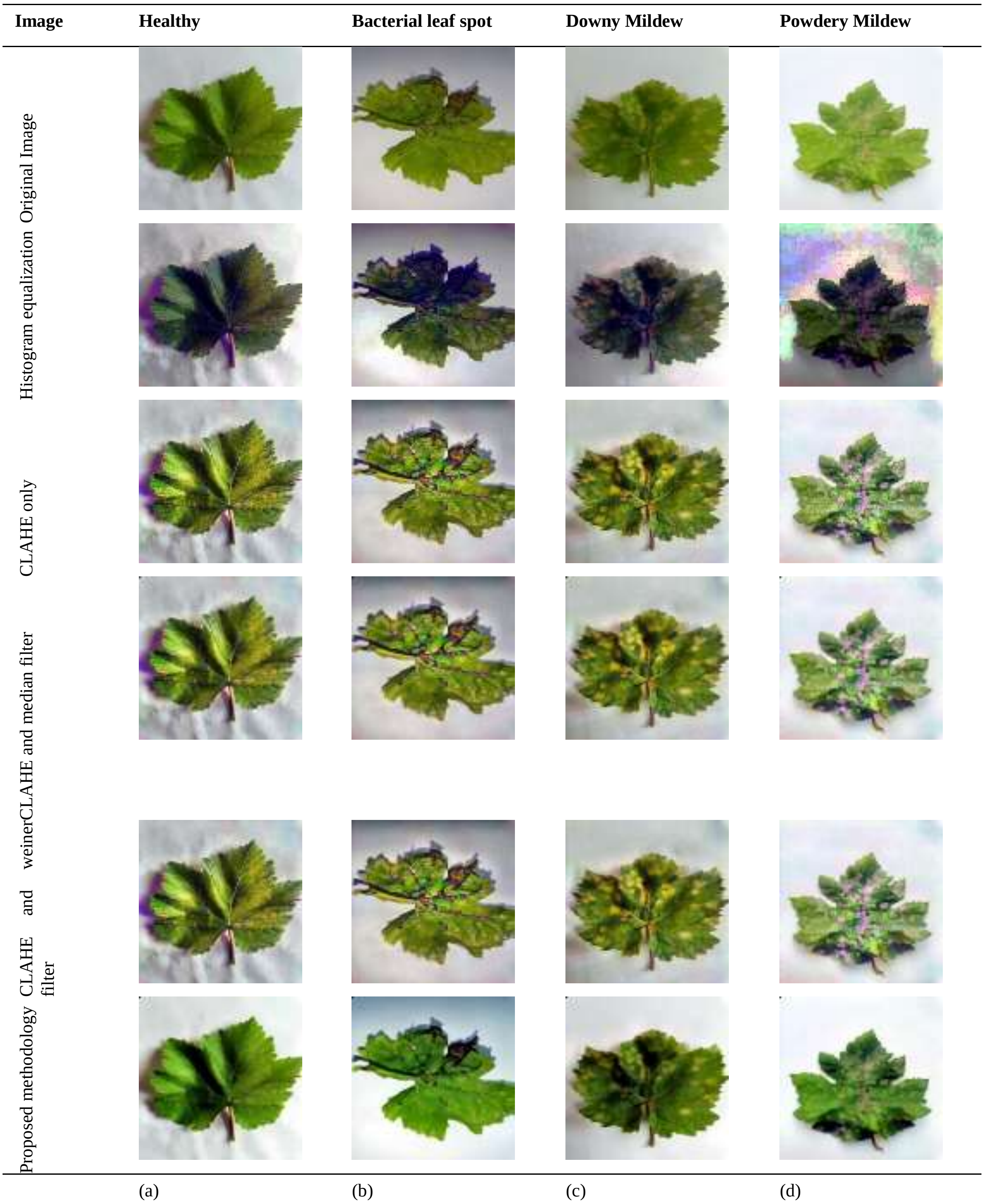


Fig. 3 Images (a) Healthy (b) Bacterial leaf (c) Downy Mildew (d) Powdery Mildew

For the purpose of evaluation of proposed methodology, parameter analysis is performed. In the thesis work, certain parameters like Entropy, Peak Signal to Noise Ratio (PSNR), Feature Similarity Index Matrix (FSIM), Spectral Similarity Index Matrix (SRSIM), Mean Absolute Error (MAE) and Universal Quality Index (UQI) parameters are evaluated for examining efficient enhancement. All these performance parameters contribute their own independent significance while representing efficient enhancement using proposed methodology.

4.1 Mean Square Error (MSE)

The MSE signifies a technique that measures the average of the squared deviations between similar pixel values in order to quantify the difference between two images. Since the squaring procedure makes MSE especially sensitive to large pixel inequalities. The measure is consistent across all pixel positions.

4.2 Peak Signal to Noise Ratio (PSNR)

The Peak Signal-to-Noise Ratio (PSNR) is a performance parameter calculated for evaluating quality of an image by examining ratio between maximum value and any type of noise present in the image. For grape leaf images, PSNR is used in assessing the image quality for accurate analysis and diagnosis. PSNR is observed while with comparison of original image and enhanced image. Higher value of PSNR signifies higher quality.

4.3 Entropy

Entropy signifies measure of the randomness present in a data source. In grape leaf images, entropy is used to examine the extent of information present in an image. It is one of the useful feature in analyzing the grape leaf image with the help of texture and patterns present. If the value of entropy is higher it represents large complexity present in image texture. It is associated with certain characteristics of grape leaf image.

4.4 Mean Absolute Error (MAE)

The Mean Absolute Error (MAE) is one of the parametric quantity used for evaluation of enhancement for grape leaf images. It signifies average magnitude between the absolute differences between the enhanced and original image. Higher values of MAE in enhanced grape leaf image, indicates that there are artifacts or distortions introduced in enhancement process that deviates the original image.

4.5 Structural Similarity Index Matrix (SSIM)

The SSIM indicates a metric intended for quantifying the structural similarity between two images. Three main factors are used by SSIM to assess image quality: structure comparison, contrast comparison, and brightness comparison. The metric calculates the mean, variance, and covariance of pixel intensities in corresponding regions of the two images under comparison by computing local statistics inside sliding windows over the image.

4.6 Feature Similarity Index Matrix (FSIM)

The Feature Similarity Index Matrix (FSIM) is a parameter used for evaluating the similarity between two images based on their low-level features, such as gradients, brightness, and textures. In the context of grape leaf images, FSIM can be useful for assessing the quality of enhanced images. The FSIM value ranges from 0 to 1, with higher values indicating greater similarity between the images in terms of their low-level features.

4.7 Riesz Tranform Based Similarity Index Matrix (RFSIM)

RFSIM is an evaluation matric that uses first-order and second-order Riesz transform coefficients. This similarity metric is a feature-based image quality evaluation measure. It is particularly efficient at collecting factors that are essential for processing visual data in humans because it enables the extraction of local amplitude, phase, and orientation information from images.

4.8 Visual Saliency Index (VSI)

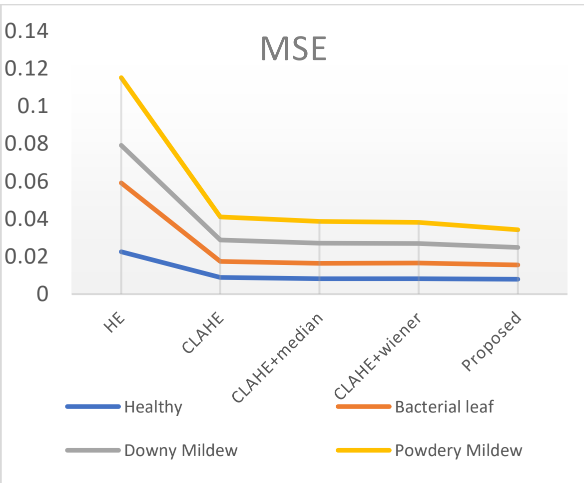
VSI is a measure for evaluating the grape leaf image quality. The fundamental principle of the VSI indicates the measure that visually prominent sections of an image have a stronger impact on perceived image quality than less salient areas because the human visual system gives different regions of an image varying amounts of attention.

With the context of above parameters, the performance of proposed methodology is examined and noted in table 1. It has been found that all parameters have performed better in comparison with other enhancement techniques.

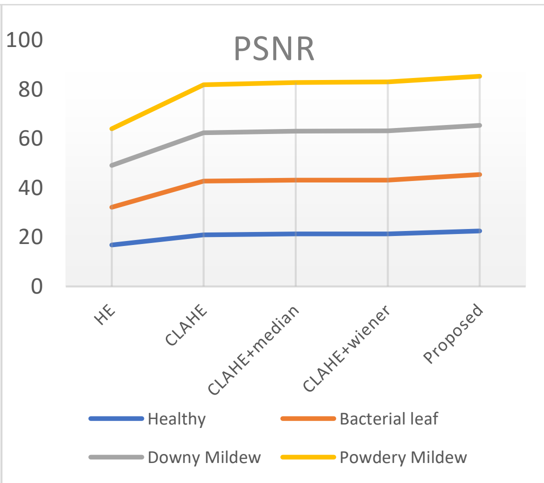
Table. 1 Comparative analysis of various enhancement methods with respect to proposed methodology

Method		MSE	PSNR	Entropy	MAE	SSIM	FSIM	RFSIM	AMBE	VSI
Histogram Equalization	Healthy	0.0225	16.8266	5.8755	0.1267	0.9970	0.9813	0.9830	0.0329	0.9812
	Bacterial leaf	0.0366	15.3020	5.8585	0.1517	0.9950	0.9932	0.9717	0.0960	0.9859
	Downy mildew	0.0230	16.9873	5.9873	0.1250	0.9968	0.9916	0.9852	0.0459	0.9859
	Powdery Mildew	0.0360	14.8637	5.6928	0.1559	0.9954	0.9843	0.9682	0.0632	0.9848
CLAHE	Healthy	0.0089	20.9056	7.3381	0.0666	0.9989	0.9847	0.9859	0.0459	0.9861
	Bacterial leaf	0.0085	21.8231	7.4335	0.0620	0.9990	0.9774	0.9853	0.0133	0.9868
	Downy mildew	0.0114	19.5721	7.4535	0.0743	0.9985	0.9871	0.9819	0.0445	0.9831
	Powdery Mildew	0.0123	19.5680	7.2662	0.0772	0.9985	0.9850	0.9817	0.0415	0.9885
CLAHE + median filter	Healthy	0.0082	21.2631	7.2850	0.0642	0.9989	0.9832	0.9873	0.0454	0.9865
	Bacterial leaf	0.0081	21.9376	7.4161	0.0610	0.9990	0.9777	0.9870	0.0162	0.9864
	Downy mildew	0.0107	19.8323	7.4243	0.0724	0.9986	0.9846	0.9836	0.0441	0.9832
	Powdery Mildew	0.0116	19.7799	7.2250	0.0754	0.9985	0.9831	0.9836	0.0415	0.9884
CLAHE + Weiner filter	Healthy	0.0082	21.2689	7.3604	0.0647	0.9989	0.9836	0.9879	0.0457	0.9868
	Bacterial leaf	0.0083	21.8964	7.3064	0.0638	0.9990	0.9791	0.9879	0.0068	0.9874
	Downy mildew	0.0104	19.9628	7.4398	0.0717	0.9986	0.9849	0.9846	0.0442	0.9838
	Powdery Mildew	0.0112	19.9317	7.2190	0.0742	0.9985	0.9839	0.9846	0.0412	0.9889
Proposed methodology	**Healthy**	**0.0079**	**22.5030**	**7.4598**	**0.0212**	**0.9996**	**0.9934**	**0.9896**	**0.0331**	**0.9980**
	Bacterial leaf	**0.0076**	**22.9022**	**7.6446**	**0.0171**	**0.9997**	**0.9942**	**0.9889**	**0.0039**	**0.9982**
	Downy mildew	**0.0093**	**19.9559**	**7.5058**	**0.0528**	**0.9996**	**0.9952**	**0.9871**	**0.0399**	**0.9983**
	Powdery Mildew	**0.0094**	**19.9329**	**7.2763**	**0.0190**	**0.9999**	**0.9948**	**0.9898**	**0.0262**	**0.9988**

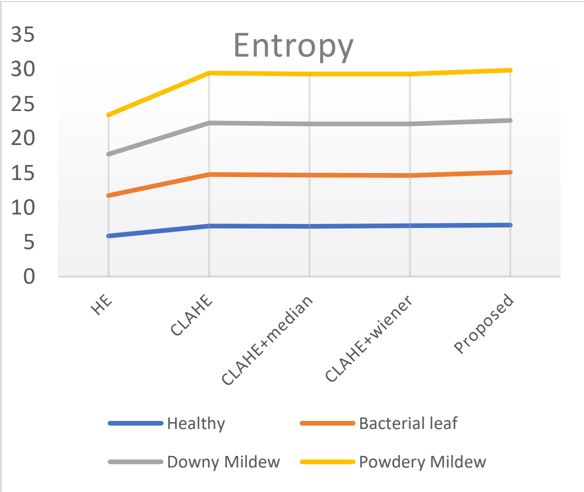
With the context of above table, the performance of proposed methodology illustrated using bar graphs as mentioned in fig. 4. It has been found that all parameters have performed better using proposed methodology in comparison with other enhancement techniques.



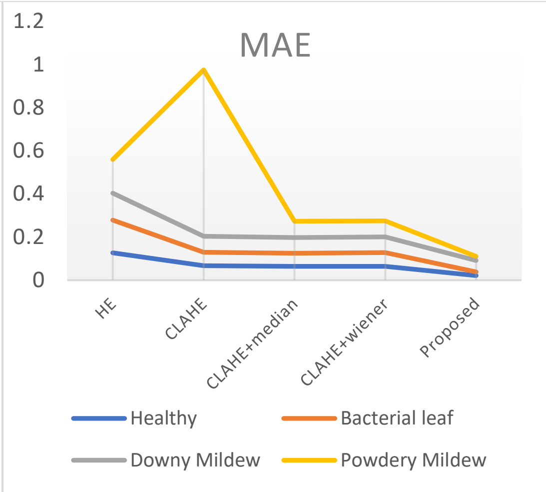
(a)



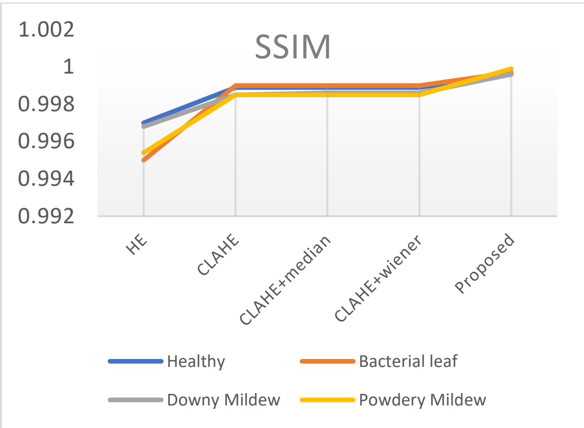
(b)


Entropy
35
30
25
20
15
10
5
0
HE
CLAHE
CLAHE+median
CLAHE+wiener
Proposed
Healthy
Bacterial leaf
Downy Mildew
Powdery Mildew

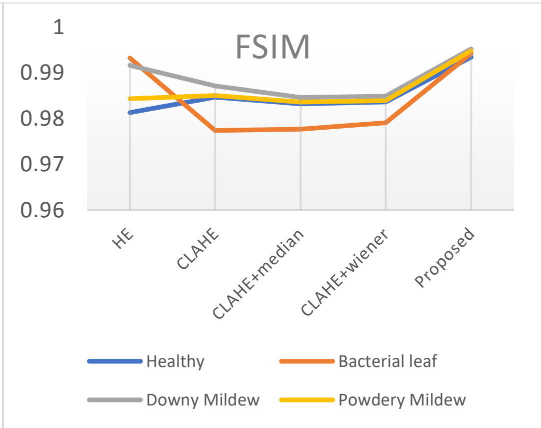
(c)


MAE
1.2
1
0.8
0.6
0.4
0.2
0
HE
CLAHE
CLAHE+median
CLAHE+wiener
Proposed
Healthy
Bacterial leaf
Downy Mildew
Powdery Mildew

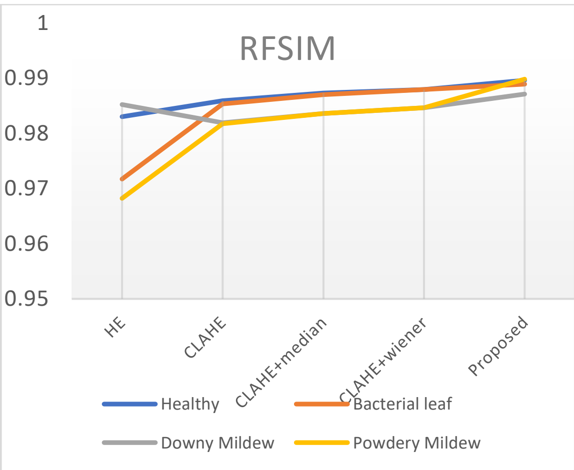
(d)


SSIM
1.002
1
0.998
0.996
0.994
0.992
HE
CLAHE
CLAHE+median
CLAHE+wiener
Proposed
Healthy
Bacterial leaf
Downy Mildew
Powdery Mildew

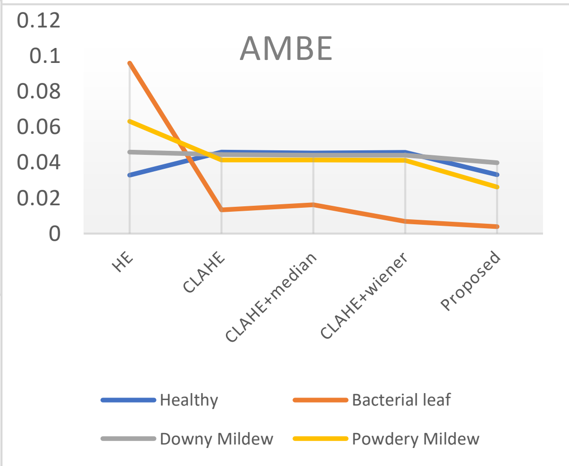
(e)


FSIM
1
0.99
0.98
0.97
0.96
HE
CLAHE
CLAHE+median
CLAHE+wiener
Proposed
Healthy
Bacterial leaf
Downy Mildew
Powdery Mildew

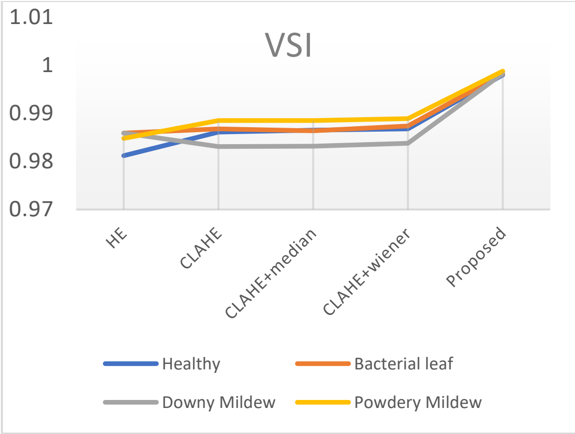
(f)


RFSIM
1
0.99
0.98
0.97
0.96
0.95
HE
CLAHE
CLAHE+median
CLAHE+wiener
Proposed
Healthy
Bacterial leaf
Downy Mildew
Powdery Mildew

(g)


AMBE
0.12
0.1
0.08
0.06
0.04
0.02
0
HE
CLAHE
CLAHE+median
CLAHE+wiener
Proposed
Healthy
Bacterial leaf
Downy Mildew
Powdery Mildew

(h)



(i)

Fig. 4 Graphical representation of different parameters (a) MSE (b) PSNR (c) Entropy (d) MAE (e) SSIM (f) FSIM (g) RFSIM (h) AMBE (i) VSI

5. Conclusion

This study successfully demonstrated the effectiveness of image enhancement techniques for grape leave images through proposed methodology. The proposed enhancement methodology was rigorously assessed using a combination of structural, perceptual, and error-based metrics including SSIM, FSIM, PSNR, AMBE, MAE, and MSE to provide a holistic evaluation of image quality improvement. In conclusion, this research contributes to the advancement of agricultural image processing by providing an effective enhancement solution for grape leave images, validated through rigorous quantitative evaluation using multiple complementary metrics that ensure both perceptual quality and analytical accuracy are maintained throughout the enhancement process.

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