Precision in Pixels: Enhancing Images of Medicinal and Aromatic Leaves

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ABSTRACT

The application of digital image processing to medicinal and aromatic leaves has become increasingly important in industries such as pharmaceuticals, cosmetics, and food, as leaf quality directly influences their usability and market value. This study investigates various image enhancement techniques applied to the DIMPSAR and MAP 177 Medicinal Leaf Datasets to improve visual quality, facilitating better feature extraction and analysis. Methods such as contrast enhancement, edge enhancement, sharpening, noise reduction, morphological operations, High Dynamic Range (HDR) enhancement, denoising and restoration, and color enhancement are systematically evaluated based on performance metrics such as Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), and Root MSE (RMSE). The results indicate that Linear Contrast Stretching (LCS) and median filtering are the most effective techniques, offering significant contrast and noise reduction improvements while preserving essential structural leaf details. Additionally, techniques such as white balance and unsharp masking enhance image consistency and sharpness, whereas Histogram Equalization (HE) and tone mapping introduce distortions that degrade image quality, limiting their applicability. Lastly, edge detection and morphological operations, primarily used for structure extraction, were found to amplify noise and distortions rather than improve image clarity.

Keywords-medicinal leaves; aromatic leaves; leaf image enhancement; digital image processing

I. INTRODUCTION

Digital image processing has become useful to various information processing systems that rely on enhancing and extracting valuable information from images. Typically, digital images consist of a matrix of pixels arranged systematically in a rectangular display, with rows determining the height and columns determining the width of the image [1]. With the rapid advancement of digital imaging technologies, both the volume and complexity of image data have significantly increased [2], driving the development of advanced image processing techniques capable of handling large-scale digital datasets efficiently. Among the industries interested in digital image processing are the Pharmaceuticals, Cosmetics, and Food industries for medicinal and aromatic leaves. This is because the image condition of leaves can be linked to their quality and properties, which in turn affects their market value. Since the global market for herbal medicine is projected to reach $411.2 billion by 2026 [3], reliable identification and quality assessment of medicinal plants is of utmost importance.

In order to achieve reliable digital image processing, several image enhancement techniques are employed, refining image data by suppressing unwanted distortions and emphasizing specific features for subsequent analysis. These techniques can be broadly categorized into spatial- and frequency-domain methods [4]. Spatial domain methods operate directly on the pixel values, whereas frequency domain methods involve transforming the image into the frequency domain, modifying the transform coefficients, and performing an inverse transformation. Recent studies have demonstrated that advanced enhancement methods can significantly improve plant species identification accuracy, achieving up to 98% under controlled conditions [5].

This study focuses on the enhancement of medicinal and aromatic leaf images, with the primary objective of improving visual quality and facilitating more effective feature extraction for accurate analysis and classification. Among the processing techniques employed were color enhancement techniques, such as color adjustment, saturation enhancement, and white balance, used to improve the visual quality of images by adjusting the color, making the images look realistic and reflect the true colors of the leaves [6]. Furthermore, contrast enhancement techniques such as Contrast Limited Adaptive Histogram Equalization (CLAHE), Histogram Equalization (HE), Linear Contrast Stretching (LCS), and Global Contrast Enhancement (GCE) are used to improve both local and global contrast, making important structural details in the leaf more distinguishable [7]. Edge enhancement techniques, such as gradient, Laplacian, Prewitt, Roberts, and Sobel operators, are used to detect and enhance the edges in an image, improving the sharpness and clarity of the leaf image, which is important for accurate feature extraction and classification tasks. In addition, High Dynamic Range (HDR) enhancement techniques, such as tone mapping, are employed to preserve details across varying brightness and contrast levels.

Additionally, morphological operations, such as BlackHat, closing, dilation, erosion, opening, and TopHat, modify image structure and shape, aiding in noise removal, gap filling, and boundary smoothing, further enhancing leaf image quality. Noise-reduction methods such as anisotropic diffusion, bilateral, Gaussian, and median filtering reduce unwanted noise while preserving essential details, ensuring the images remain artifact-free. Sharpening techniques, including classical sharpening and unsharp masking, enhance edges and fine details. Denoising and restoration methods, such as inverse filtering and total variation denoising, are applied to recover original image quality by removing noise and distortions, making the images more suitable for downstream analysis.

II. LITERATURE SURVEY

Several studies have explored the use of machine learning to automate the process of leaf image classification and identification, achieving promising results when combined with appropriate enhancement methods.

In [8], various machine learning approaches, including Naïve Bayes Classifier (NBC), Classification and Regression Tree (CART), K-Nearest Neighbor (KNN), and Probabilistic Neural Network (PNN), were employed for classifying medicinal and aromatic plants based on leaf shape, gray level, and fractal features. In another study, authors in [9] developed an automated system for recognizing 24 medicinal plant species using computer vision and machine learning, extracting features such as length, width, perimeter, and color. Among the models considered, the Random Forest classifier with 10-fold cross-validation achieved the highest accuracy of 90.1%, outperforming KNN, Naive Bayes, and Support Vector Machines (SVM). In addition, authors in [10] developed an enhancement method combining local and GCE, haze reduction, decorrelation stretching, CLAHE filtering, and various denoising techniques, with their approach effectively enhancing low-contrast leaf images.

The study in [11] introduced an image classification approach to address the challenge of low-contrast plant images, where enhanced images were used as input to a Quantum Convolutional Neural Network (QCNN) model, achieving 97.64% accuracy, 98.36% specificity, 98% precision, 96.98% recall, and 98.18% F1-score, outperforming conventional Convolutional Neural Networks (CNNs). Similarly, authors in [12] proposed a Bacterial Foraging Optimization-based Radial Basis Function Neural Network (BRBFNN) for leaf disease detection. Moreover, authors in [13] applied machine learning to classify six varieties of medicinal plant leaves: Tulsi, Peppermint, Bael, Lemon Balm, Catnip, and Stevia. The dataset was collected through multispectral and digital imaging, with preprocessing steps including cropping, gray-level transformation, and edge/line detection using the Sobel filter. A total of 65 features, combining texture, run-length matrix, and multispectral information, were extracted, while feature optimization using a chi-square selection approach reduced the number of features to 14. This study used five classifiers, including Multi-Layer Perceptron, Logit-Boost, Bagging, Random Forest, and Simple Logistic, to test the dataset. In [14], a computer-aided classification system characterized different medicinal plant leaves using texture features derived from Laws mask analysis, achieving accurate classification across five species with SVM. Another study in [15] investigated the use of feature vectors from both sides of leaves as morphological features for improved identification, extending the approach to also examine dry leaves. Another work in [16] evaluated four pretrained CNN models (ResNet-101, ResNet-50, Inception-ResNet-v2, and VGG-19) for detecting and classifying pineapple fruits under complex backgrounds and varying lighting conditions. Lastly, in [17], a Random Forest-based approach was implemented for medicinal plant identification using color, texture, and shape features, while authors in [18] proposed a machine learning-based framework integrating feature extraction, classification, and a user-friendly interface to allow users to upload images and obtain identification results.

Overall, these works underscore the potential of combining machine learning with image processing to automate leaf classification, which has broad implications for sectors such as agriculture, pharmaceuticals, and biodiversity conservation.

III. DATASET

In this work, DIMPSAR [19] and MED 117 Medicinal Plant Leaf Dataset [20] were used. The DIMPSAR dataset comprises high-resolution images of 40 species of healthy medicinal plants and 80 healthy medicinal leaves. Each species includes between 60 and 100 images, captured using a Samsung S9+ mobile camera and a printer scanner, and organized in folders that are named according to the botanical/scientific names of the plants. The images are slightly rotated and tilted to increase variability during the training of machine learning and deep learning models.

The MED 117 dataset includes leaf images of 117 medicinal plant species native to Assam, India. The images were collected from various medicinal gardens managed by government, public, and private institutions. To ensure high-quality and consistent images, videos of 10 to 15 seconds duration are captured for two to three leaves of each species against a white background using a Single-Lens Reflex (SLR) Canon Camera. Individual frames extracted from these videos resulted in approximately 77,700 JPEG images. Each folder in the dataset is labeled with both the scientific and common names of the plant species, facilitating easy identification and organization.

IV. IMAGE ENHANCEMENT TECHNIQUES

In this study, various image enhancement techniques have been employed, including contrast enhancement, edge enhancement, sharpening, noise reduction, morphological operations, HDR, denoising and restoration, and color enhancement.

A. Contrast Enhancement

Contrast enhancement technique in image processing is used to improve the overall quality and visibility of an image by adjusting its contrast and brightness [21]. In this study, five contrast enhancement techniques have been evaluated:

- LCS, which enhances image quality and visibility by adjusting the difference between the darkest and brightest areas in the image [22].
- HE, which is a nonlinear stretching process that enhances the contrast of an image by redistributing image intensity [23] and is especially effective in images with low contrast or poor illumination.
- CLAHE, which divides an image into tiles and applies HE to each tile independently [24].
- GCE, which is used to improve an image's overall visibility and clarity by adjusting the intensity values. This technique is useful for images with narrow intensity ranges, where separation of details is difficult [25].
- Local Contrast Enhancement (LCE), which increases the contrast of medium-sized areas within an image to bring out texture and detail.

B. Edge Enhancement

Edge enhancement is a digital image processing technique that is used to highlight the edges and lines present within an image by making them appear more distinct and sharper [26]. Among the edge enhancement techniques considered in this study were:

- Sobel kernel, which uses a kernel and two 3×3 convolution masks, wherein the first mask estimates the gradient in the horizontal direction and the second mask the gradient in the vertical direction [27].
- Prewitt kernel, which operates similarly to the Sobel kernel, but instead of assigning higher weights to the central pixels in its kernel, it uses equal weights for all pixels [28].
- Laplacian kernel, which is a second-order edge detection technique in which the kernel function is used to measure the similarity between two data points, which are based on the squared Euclidean distance [29].
- Robert's kernel or Roberts cross operator, which uses a 2×2 convolution kernel to detect and highlight the edges in an image [30], particularly in images with fine details.
- Gradient operator, which calculates the rate of change in pixels across an image and is particularly effective at detecting boundaries between regions of different intensities.

C. Sharpening

Sharpening is an image-processing technique that is used to enhance important features, such as edges and fine details, by increasing the contrast between adjacent pixels, making the image more distinct [31]. The specific sharpening techniques examined in this study were:

- Classical sharpening, which uses a convolution kernel with a central positive value surrounded by negative values, enhances the edges by subtracting the surrounding pixel values from the central pixel value, thereby increasing the contrast of the edges
- Unsharp masking, in which masking image enhancement is achieved by creating a blurred version of the original image and subtracting it from the original image. The final image generation can be summarized in the following representation:

  $$Sharpened = original + a(original - blurred) \quad (1)$$

  where a is a parameter that controls the strength of the sharpening effect applied. This method effectively enhances the contrast and details in images without amplifying noise.

D. Noise Reduction

Noise reduction is a process that removes or reduces the unwanted random variations present in pixels, improving the overall quality and clarity of the image by preserving important features [32]. The particular techniques used were:

- Median filtering, which is a nonlinear digital image processing technique involving replacing each pixel value with the median of its neighboring pixel values, defined in the kernel function [33]. Median filtering is effective in reducing the salt-and-pepper noise present in an image.
- Gaussian filtering, which is a linear smoothing process that reduces the noise and blurs in an image by applying a weighted average value of neighboring pixels based on the Gaussian function, smoothening the image by reducing high-frequency signals [34].
- Bilateral filtering, in which each pixel value is replaced with a neighboring pixel using a weighted average dependent on intensity difference and spatial distance between the pixels [35].

- Anisotropic diffusion, which selectively smooths images while preserving and enhancing edges and important structural features.

E. Morphological Operations

Morphological operations are a set of techniques in image processing that apply a structuring element to an input image, modifying the shape and structure of the image. The operations used in this study were:

- Erosion, which uses a structuring element to scan the image and then shrinks the boundaries of the foreground object, removing pixels from their boundaries. This operation removes small noise, detaches connected objects, and removes boundaries [36].
- Dilation, which increases the boundaries of objects in an image, making them larger and filling small holes [36], and uses a structuring element, which is a small matrix, to scan the input image.
- Opening, which combines two techniques: first, the erosion technique to remove small objects and noise in the image, and then the dilation technique to restore the original shape of the objects [36].
- Closing, which uses dilation to fill small holes and gaps in the image and then applies the erosion technique to restore the original shape of the object [36].
- TopHat Transform, which extracts small elements and details from an image by subtracting the opening or closing of the image from an input image [37]. This operation is useful for highlighting bright objects on a dark background or vice versa.
- BlackHat, which extracts dark features from the images, is computed by subtracting the closing operations from the original image.

F. HDR Enhancement

HDR is a powerful image enhancement technique that improves the visual quality of images by adjusting brightness and contrast, especially in low-light and bright light conditions. HDR enhancement involves combining multiple versions of one image taken at different exposure levels to produce a final image with a wider range of brightness and color detail [38]. For this analysis, the tone mapping technique was used, which adjusts the brightness and contrast values of HDR images to make them look more natural with a controlled effect of the HDR technique [39].

G. Denoising and Restoration

Denoising and restoration process in image processing focuses on improving the image quality by reducing or eliminating the noise present in an image, caused by factors such as poor lighting or a low-quality camera [40]. The specific techniques employed were:

- Inverse filtering, which attempts to reverse known blurring effects using the inverse of the degradation filter; however, this method is sensitive to noise and may amplify it if not properly regularized [41].
- Total variation denoising, which is a nonlinear image restoration technique that aims to reduce the noise in an image by minimizing the total variation of the image, measured as the sum of absolute values of the image gradient. This technique is effective for removing image noise by preserving edges and details in the generated image.

H. Color Enhancement

Color enhancement is an image processing technique that focuses on improving the overall image quality and appearance by manipulating features such as color, contrast, and hue to make the images look more vibrant [42]. The techniques employed included:

- Color adjustment, which adjusts saturation, color, hue, brightness, and contrast in the image to make it look more natural and vibrant.
- Saturation enhancement, which increases the intensity of color in an image to make it look bolder. This method is useful in low-light conditions or when dealing with images that have washed-out colors.
- White balance, which corrects color temperature to ensure that neutral tones appear white, improving visual consistency across samples.

V. RESULTS AND DISCUSSION

To evaluate the image enhancement techniques used, three key metrics were utilized: Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Root Mean Squared Error (RMSE). MSE compares the difference between the corresponding pixel intensity in the original image and the enhanced image [43], and is defined as:

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (P_i - O_i)^2 \qquad (2)$$

where P_i and O_i represent the pixel intensities of the enhanced and original images, respectively, and n is the total number of pixels. PSNR is a logarithmic measure of the ratio between the signal noise power and the signal maximum power [32], with a higher PSNR value indicating a higher quality in the enhanced image [43], defined as:

$$PSNR = 10 \cdot log_{10}\left(\frac{MAX^2}{MSE}\right) \qquad (3)$$

where MAX is the maximum pixel intensity (255 for an 8-bit image). RMSE represents the square root of MSE, providing an interpretable error measure in the same units as the original pixel intensity [44]:

$$RMSE = \sqrt{MSE} \qquad (4)$$

A. Performance Analysis of Image Enhancement Techniques on DIMPSAR and MED 177 Dataset

1) Contrast Enhancement

The performance results of the contrast enhancement technique are presented in Table I, while Figure 1 illustrates the resulting enhanced image.

TABLE I. QUANTITATIVE PERFORMANCE METRICS FOR CONTRAST ENHANCEMENT TECHNIQUES

Technique	MED 177			DIMPSAR		
	MSE (dB^2)	RMSE (dB)	PSNR	MSE (dB^2)	RMSE (dB)	PSNR
LCS (RGB)	439.2	67.5	124.3	170	8.66	36.61
HE (RGB)	1,279.6	90.9	54.8	1,928	74.4	55.9
CLAHE (RGB)	244.22	14.07	25.93	595	23.4	21.19
LCE (RGB)	624.6	114.73	155.73	826	113.7	121.9
CLAHE (Gray)	474.5	84.67	95.7	732	26.2	20.07
HE (Gray)	2,789.3	50.88	14.38	2,238	44.4	15.79
LCS (Gray)	215.5	14.7	44.8	165.3	12.9	36.9
GCE (RGB)	229.02	7.65	44.23	84.7	4.34	45.63

Red-Green-Blue (RGB)

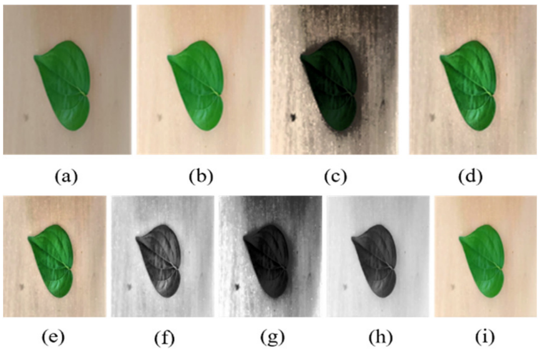


Fig. 1. Visual representation of the contrast enhancement techniques: (a) Input image, (b) LCS (RGB), (c) HE (RGB), (d) CLAHE (RGB), (e) LCE (RGB), (f) CLAHE (Gray), (g) HE (Gray), (h) LCS (Gray), and (i) GCE (RGB).

LCE (RGB) achieved the best performance with the highest PSNR value of 155.73 on the MED 177 dataset and of 121.9 on the DIMPSAR dataset, combined with MSE values of 624.6 dB^2 and 826 dB^2, respectively. Furthermore, CLAHE (Gray) demonstrated strong contrast enhancement on the MED 177 dataset with a PSNR of 95.7 and an MSE of 474.5 dB^2, while on DIMPSAR, it achieved a PSNR of 20.07 and an MSE of 732 dB^2. The colored version of CLAHE (RGB), on the contrary, exhibited a moderate performance with PSNR/MSE values of 25.93/244.22 dB^2 on MED 177 and 21.19/595 dB^2 on DIMPSAR. Thus, both CLAHE variants effectively enhanced local contrast while preserving important image details, making them suitable for adaptive enhancement applications [45]. HE (RGB) achieved the third-best PSNR value of 54.8 on MED 177 and the second-best of 55.9 on DIMPSAR, with MSE values of 1,279.6 dB^2 and 1,928 dB^2, respectively. However, HE (Gray) showed notably lower performance, with the lowest PSNR values of 14.38 and 15.79, and the highest MSE values of 2,789.25 dB^2 and 2,238.0 dB^2 in both datasets. This performance suggests over-enhancement and the introduction of artifacts, consistent with the findings in [46], where it was noted that HE may cause distortions in complex grayscale images. In addition, LCS (RGB) performed well on the MED 177 dataset, with a PSNR of 124.3 and an MSE of 439.2 dB^2, while on the DIMPSAR dataset, it yielded a PSNR of 36.61 and an MSE of 170 dB^2. In contrast, LCS (Gray) achieved a better MSE of 215.5 dB^2 but a worse PSNR value of 44.8 on the MED 177 dataset, while in the DIMPSAR dataset, it achieved a MSE of 165.3 dB^2 and a PSNR of 36.9. Lastly, GCE (RGB) attained the lowest MSE of 84.7 dB^2 and the third-best PSNR of 45.63 on the DIMPSAR dataset, and the second-best MSE of 229.02 dB^2 but the third-worst PSNR of 44.23 on MED 177. Overall, LCE (RGB) and LCS (RGB) emerged as the most effective techniques, showing superior PSNR performance on the MED 177 dataset, achieving a balance between contrast enhancement and image integrity.

2) *Edge Enhancement*

Table II presents the quantitative performance metrics achieved by the edge enhancement techniques employed, while Figure 2 presents the corresponding effects on the input image.

TABLE II. QUANTITATIVE PERFORMANCE METRICS FOR EDGE ENHANCEMENT TECHNIQUES

Technique	MED 177			DIMPSAR		
	MSE (dB^2)	RMSE (dB)	PSNR	MSE (dB^2)	RMSE (dB)	PSNR
Gradient	25,025.4	157.64	4.21	16,639.1	125.87	6.36
Laplacian	4,109.9	62.77	12.38	2,356.3	46.06	15.31
Prewitt	25,018.4	157.62	4.21	16,639.1	125.87	6.36
Roberts	25,097.3	157.88	4.2	17,114.6	127.8	6.22
Sobel	25,025.4	157.64	4.21	16,624.8	125.81	6.36

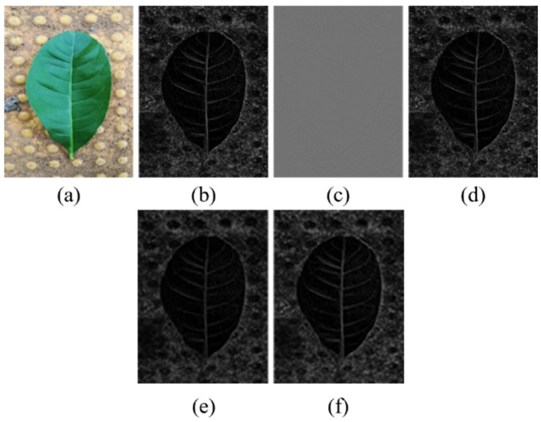


Fig. 2. Visual representation of the edge enhancement techniques: (a) Input image, (b) Gradient, (c) Laplacian, (d) Prewitt, (e) Roberts, and (f) Sobel.

The Sobel and Prewitt operators exhibited similar performance on both datasets, with MSE values of 16,624.8 dB^2 and 16,639.1 dB^2 on DIMPSAR, and 25,025.4 dB^2 and 25,018.4 dB^2 on MED 177, respectively, along with similar PSNR and RMSE values. This similarity indicates that both operators are equally effective in enhancing edges while maintaining a balance between noise reduction and detail preservation on these datasets [48], while their high MSE values suggest that they may be less suitable for images containing fine textures or intricate details.

Moreover, the Roberts operator, with an MSE of 17,114.6 dB^2 and a PSNR of 6.22 on the DIMPSAR dataset, demonstrated slightly higher noise levels but also improved PSNR, showcasing promising results for enhancing finer details. On the MED 177 dataset, Roberts achieved an MSE of 25,097.3 dB^2 and a PSNR of 4.20, showcasing significantly higher MSE compared to the other dataset. Next, the Gradient operator yielded among the highest MSE values (25,025.4 dB^2 on MED 177 and 16,639.1 dB^2 on DIMPSAR) and among the lowest PSNR values (4.21 and 6.36), indicating limited edge enhancement capability. The Laplacian operator demonstrated the best overall results, with an MSE of 2,356.3 dB^2 and a PSNR of 15.31 on DIMPSAR, and 4,109.9 dB^2 with a PSNR of 12.38 on MED 177, indicating that it balanced noise reduction and edge enhancement on both datasets.

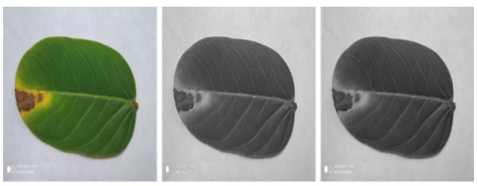
3) *Sharpening*

Table III compares the performance of two sharpening techniques: classical sharpening and unsharp masking, while Figure 3 illustrates their effect on the input image. Classical sharpening achieved an MSE of 118.93 dB^2, an RMSE of 8.26 dB, and a PSNR of 31.27 on MED 177, and an MSE of 481.99 dB^2, an RMSE of 18.58 dB, and a PSNR of 24.54 on DIMPSAR. These results indicate that the method effectively enhanced edges with a moderate level of error, but also introduced a moderate level of noise, as reflected in the PSNR values, which limits its usefulness for all applications.

On the other hand, unsharp masking demonstrated significantly better performance with an MSE of 427.21 dB^2, an RMSE of 15.68 dB, and a PSNR of 27.82 on the MED 177 dataset, and an MSE of 97.37 dB^2, an RMSE of 7.99 dB, and a PSNR of 31.99 on the DIMPSAR dataset. Thus, the unsharp masking technique provided better noise reduction and overall image quality across both datasets.

TABLE III. QUANTITATIVE PERFORMANCE METRICS FOR SHARPENING TECHNIQUES

Technique	MED 177			DIMPSAR		
	MSE (dB^2)	RMSE (dB)	PSNR	MSE (dB^2)	RMS E (dB)	PSNR
Classical Sharpening	118.93	8.26	31.27	481.99	18.58	24.54
Unsharp Masking	427.21	15.68	27.82	97.37	7.99	31.99



(a) (b) (c)

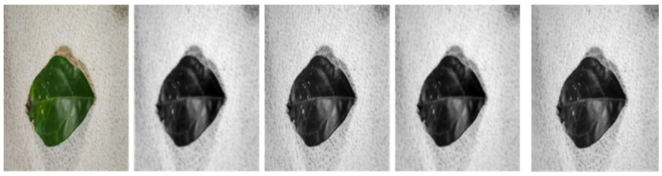
Fig. 3. Visual representation of the sharpening enhancement techniques: (a) Input image, (b) Classical sharpening, and (c) Unsharp masking.

4) *Noise Reduction*

Table IV summarizes the performance of the Noise Reduction techniques employed, while Figure 4 displays their effect on the original image.

TABLE IV. QUANTITATIVE PERFORMANCE METRICS FOR NOISE REDUCTION TECHNIQUES

Technique	MED 177			DIMPSAR		
	MSE (dB^2)	RMSE (dB)	PSNR	MSE (dB^2)	RMS E (dB)	PSNR
Anisotropic Diffusion	1,142.5	30.4	19.61	609.39	22.06	22.3
Bilateral Filtering	1,145.2	30.24	19.78	557.95	20.83	22.9
Gaussian Filtering	1,087.4	29.05	20.37	382.46	16.44	25.54
Median Filtering	1,034.9	28.07	20.86	17.93	3.77	37.92



(a) (b) (c) (d) (e)

Fig. 4. Visual representation of the sharpening enhancement techniques: (a) Input image, (b) Anisotropic, (c) Gaussian, (d) Bilateral, and (e) Median.

Gaussian filtering provided balanced results, with MSE, RMSE, and PSNR values of 1,087.4 dB^2, 29.05 dB, and 20.37 on MED 177, and 382.46 dB^2, 16.44 dB, and 25.54 on DIMPSAR, respectively. This performance indicates effective noise reduction based on the relatively good PSNR values, but the higher MSE and RMSE values suggest that the technique introduces some noise in areas with high-frequency details [49].

Bilateral filtering achieved an MSE of 1,145.2 dB^2, RMSE of 30.24 dB, and PSNR of 19.78 on MED 177, and 557.95 dB^2, 20.83 dB, and 22.90 on DIMPSAR, respectively. While this method preserves edges, its higher MSE and RMSE values indicate suboptimal effectiveness in minimizing overall distortion compared to other techniques, while its lower PSNR value suggests that the signal-to-noise ratio is not adequate, thus affecting the visual quality of the enhanced image.

Furthermore, anisotropic diffusion yielded similar performance, with MSE 1,142.5 dB^2, RMSE 30.40 dB, and PSNR 19.61 on MED 177, and MSE 609.39 dB^2, RMSE 22.06 dB, and PSNR 22.30 on DIMPSAR. Although it is known for reducing noise while preserving edges, the higher MSE and RMSE values indicate higher distortion levels, while the lower PSNR values suggest lower effectiveness in improving the overall image quality.

Lastly, median filtering outperformed the other techniques, achieving the lowest MSE values (1,034.9 dB^2 on MED 177 and 17.93 dB^2 on DIMPSAR) and the highest PSNR values (20.86 and 37.92, respectively), demonstrating its high ability to reduce noise while preserving important image details, resulting in minimal distortion and high signal-to-noise ratios.

5) *Morphological Operations*

Table V summarizes the performance results for the morphological operations employed, and Figure 5 illustrates the corresponding effects on an example input image.

TABLE V. QUANTITATIVE PERFORMANCE METRICS FOR MORPHOLOGICAL OPERATIONS TECHNIQUES

Technique	MED 177			DIMPSAR		
	MSE (dB^2)	RMSE (dB)	PSNR	MSE (dB^2)	RMSE (dB)	PSNR
BlackHat	25,604.9	159.5	4.1	19,397.6	136.8	5.57
Closing	895.33	26.19	21.34	328.99	15.46	26.02
Dilation	979.84	27.87	20.43	455.3	19.32	23.38
Erosion	1,163.6	30.59	19.57	585.73	21.79	22.4
Opening	1,142.7	29.57	20.41	362.71	15.4	26.55
TopHat	25,531.1	159.3	4.12	18,919.1	135.0	5.71

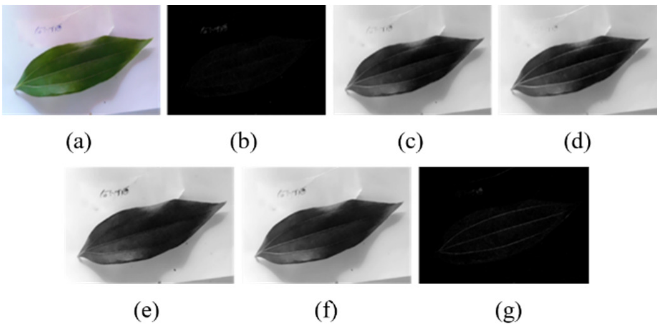


Fig. 5. Visual representation of the morphological operations: (a) Input image, (b) BlackHat, (c) Closing, (d) Dilation, (e) Erosion, (f) Opening, and (g) TopHat.

On the DIMPSAR dataset, BlackHat yielded an MSE of 19,397.6 dB^2, an RMSE of 136.86 dB, and a PSNR of 5.57, while TopHat achieved an MSE of 18,919.1 dB^2, an RMSE of 135.0 dB, and a PSNR of 5.71. On the MED 177 dataset, BlackHat achieved an MSE of 25,604.9 dB^2, an RMSE of 159.5 dB, and a PSNR of 4.1, while TopHat achieved an MSE of 25,531.1 dB^2, an RMSE of 159.3 dB, and a PSNR of 4.12. These high MSE and RMSE values and low PSNR values indicate minor distortion in the enhanced images, suggesting that although these operations effectively highlight small details, they introduce noise or artifacts, making them less suitable for applications requiring high overall image quality.

On the DIMPSAR dataset, the closing operation recorded an MSE of 328.99 dB^2, an RMSE of 15.46 dB, and a PSNR of 26.02, while the opening operation yielded an MSE of 362.71 dB^2, an RMSE of 15.4 dB, and a PSNR of 26.55. On the MED 177 dataset, the closing operation achieved an MSE of 895.33 dB^2, an RMSE of 26.19 dB, and a PSNR of 21.34, while the opening operation achieved an MSE of 1,142.7 dB^2, an RMSE of 29.57 dB, and a PSNR of 20.41. These metrics indicate that both operations effectively reduced noise and preserved key details, resulting in higher image quality [50].

On the DIMPSAR dataset, dilation yielded an MSE of 455.3 dB^2, an RMSE of 19.32 dB, and a PSNR of 23.38, while erosion showed an MSE of 585.73 dB^2, an RMSE of 21.79 dB, and a PSNR of 22.4. On the MED 177 dataset, dilation achieved an MSE of 979.84 dB^2, an RMSE of 27.87 dB, and a PSNR of 20.43, whereas erosion achieved an MSE of 1,163.69 dB^2, an RMSE of 30.59 dB, and a PSNR of 19.57. These results indicate that although these operations effectively modify object structure in the enhanced image, they introduce slight distortion.

Overall, the results show that closing and opening operations offer the best balance between noise reduction and detail preservation across both datasets. BlackHat and TopHat effectively enhance small structures but introduce considerable distortion. Dilation and erosion perform moderately, introducing some distortion but remaining useful for specific applications where such effects are acceptable.

6) *HDR Enhancement*

Table VI lists the resulting metrics evaluating the performance of the tone mapping HDR enhancement technique, while Figure 6 illustrates its effect on an example input image. On the MED 177 dataset, tone mapping achieved an MSE of 751.33 dB^2, an RMSE of 27.25 dB, and a PSNR of 19.47, while on the DIMPSAR dataset, it achieved an MSE of 1,044.43 dB^2, an RMSE of 32.1 dB, and a PSNR of 18.07. These results indicate that tone mapping effectively enhanced the dynamic range of the image, but introduced moderate levels of error, which limits its ability to preserve fine details and fully minimize distortion.

TABLE VI. QUANTITATIVE PERFORMANCE METRICS FOR HDR ENHANCEMENT TECHNIQUES

Technique	MED 177			DIMPSAR		
	MSE (dB^2)	RMSE (dB)	PSNR	MSE (dB^2)	RMSE (dB)	PSNR
Tone Mapping	751.33	27.25	19.47	1,044.43	32.11	18.07

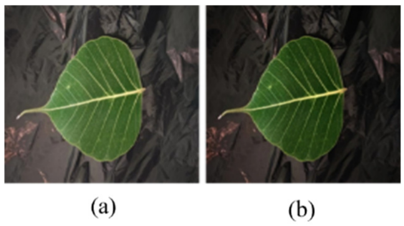


Fig. 6. Visual representation of the HDR enhancement technique: (a) Input image, and (b) Tone mapping.

7) *Color Enhancement*

The quantitative metrics in Table VII compare three color enhancement techniques: color adjustment, saturation enhancement, and white balance. Figure 7 depicts a visual representation of each effect on an example input image.

Color adjustment, which modifies image brightness and contrast, achieved an MSE of 917.18 dB^2, an RMSE of 30.11 dB, and a PSNR of 18.61 on MED 177, while on DIMPSAR it achieved an MSE of 814.38 dB^2, an RMSE of 28.17 dB, and a PSNR of 19.27, with the relatively low PSNR values suggesting limited effectiveness in enhancing the image and the introduction of possible distortion.

Saturation enhancement showed significantly lower MSE values of 237.24 and 191.19 dB^2, RMSE values of 13.21 and 11.96 dB, and PSNR values of 27.63 and 27.92 for the MED 177 and DIMPSAR datasets, respectively. These results indicate that this technique effectively improved color intensity while maintaining a reasonable balance between error and detail preservation.

White balance demonstrated the best performance, achieving the lowest MSE of 128.36 and 162.69 dB^2, RMSE of 8.88 and 8.90 dB, and the highest PSNR of 32.40 and 32.17 for the MED 177 and DIMPSAR datasets, respectively. These metrics confirm that White Balance minimized color distortion while preserving important details, providing the most reliable enhancement overall.

TABLE VII. QUANTITATIVE PERFORMANCE METRICS FOR COLOR ENHANCEMENT TECHNIQUES

Technique	MED 177			DIMPSAR		
	MSE (dB^2)	RMSE (dB)	PSNR	MSE (dB^2)	RMSE (dB)	PSNR
Color Adjustment	917.18	30.11	18.61	814.38	28.17	19.27
Saturation Enhancement	237.24	13.21	27.63	191.19	11.96	27.92
White Balance	128.36	8.88	32.40	162.69	8.90	32.17

(a) (b) (c) (d)

Fig. 7. Visual representation of the color enhancement techniques: (a) Input image, (b) Color adjustment, (c) Saturation enhancement, and (d) White balance.

8) *Restoration and Denoising*

The performance metrics in Table VIII compare two restoration and denoising methods: inverse filtering and total variation denoising. Figure 8 illustrates the visual effect of each method employed. Inverse filtering achieved an MSE of 1,124.8 dB^2, an RMSE of 29.87 dB, and a PSNR of 19.92 on MED 177, and an MSE of 502.62 dB^2, an RMSE of 19.64 dB, and a PSNR of 23.53 on DIMPSAR. These results indicate effective noise reduction and image detail restoration, achieving a balance between error reduction and detail preservation [51].

On the other hand, total variation denoising achieved an MSE of 1,149.71 dB^2, an RMSE of 30.51 dB, and a PSNR of 19.61 on MED 177, and an MSE of 557.3 dB^2, an RMSE of 20.56 dB, and a PSNR of 23.12 on DIMPSAR. Although this technique also reduces noise, the slightly higher MSE and RMSE indicate greater distortion compared with inverse filtering. Additionally, the PSNR value is slightly lower, indicating a slightly less favorable signal-to-noise ratio, suggesting that while total variation denoising is effective in smoothing the image and reducing noise, it may not be as effective in preserving fine details and minimizing overall errors.

TABLE VIII. QUANTITATIVE PERFORMANCE METRICS FOR DENOISING RESTORATION TECHNIQUES

Technique	MED 177			DIMPSAR		
	MSE (dB^2)	RMSE (dB)	PSNR	MSE (dB^2)	RMSE (dB)	PSNR
Inverse Filtering	1,124.8	29.87	19.92	502.62	19.64	23.53
Total Variation Denoising	1,149.7	30.51	19.61	557.3	20.56	23.12

(a) (b) (c)

Fig. 8. Visual representation of the restoration and denoising techniques: (a) Input image, (b) Inverse filtering, and (c) Variation denoising.

VI. CONCLUSION

This comprehensive study demonstrates the efficacy of various image-processing techniques in enhancing and classifying images of medicinal and aromatic leaves, with significant uses in both research and industry applications. By systematically evaluating multiple enhancement methods across the DIMPSAR and MAP 177 Medicinal Leaf datasets, the study identified optimal approaches for improving image quality.

The results reveal a clear distinction in performance among the techniques. Linear Contrast Stretching (LCS) and median filtering emerged as top-performing methods, providing substantial improvements in contrast and noise reduction while preserving critical image details. White balance and unsharp masking also demonstrated strong performance, effectively enhancing color consistency and sharpness. However, methods such as Histogram Equalization (HE) and tone mapping, while effective under specific conditions, often introduced distortions that limit their suitability in applications requiring high fidelity. Moreover, edge detection and morphological operations techniques tended to increase noise and distort the image, making them less ideal for broad enhancement purposes. Therefore, the choice of enhancement technique should depend on the specific application, balancing the desired level of enhancement with the acceptable degree of distortion.

Future research should focus on developing hybrid methods that integrate the strengths of multiple techniques to achieve improved results. Furthermore, exploring deep learning approaches could further enhance classification accuracy, especially when applied to more complex or diverse leaf datasets. Additionally, investigating the applicability of these techniques to a broader range of plant species could expand the utility of the proposed work beyond medicinal and aromatic plants. Lastly, developing real-time image-processing systems for on-site leaf analysis in agricultural and pharmaceutical settings represents another promising direction, potentially transforming field research and industrial quality-control processes.

DATA AVAILABILITY

Data sharing does not apply to this article, as no datasets were generated during the current study.

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