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# Quick Leaf-LS 1.5: Software for Grading of the Leaf Damage Caused by Leaf Spot Diseases using Digital Image Processing

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## ABSTRACT

For mango (Mangifera Indica L.) fruit tree crops, a major tropical fruit of economic value, leaf spot diseases cause a significant decrease in yield and quality. The conventional procedure of assessing the degree of disease damage in leaf tissue employs manual grading, a time-consuming process that is subjective and prone to human error. Present study describe the software developed for quick, precise, and automated implementation of digital image processing techniques using MATLAB for leaf spot damage grading. The software can use both scanned and photographed images of plant leaves to measure disease severity. This software provided an integrated approach for image pre-processing, segmentation and quantification algorithms using feature extraction to yield objective grading. Software validation yielded good accuracy with R2 =0.997, mean error rate =3.39%, mean accuracy rate=96.61%, RMSE= 1.260 and MAE= 0.619. Results showed that the system exhibits a very high accuracy in detecting and quantifying leaf spot lesions, which makes it a reliable tool for plant pathologists and crop scientists. This innovation has potential applications in disease monitoring, breeding programs, and precision agriculture.

**Keywords:** Leaf spot disease, Mango, Digital image processing, MATLAB, Automated grading, Plant pathology

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## INTRODUCTION

Mango is one of the most important fruit crops in tropical and subtropical areas. Its economic and nutritional importance makes it a foundation of horticultural industries across the world. Foliar diseases, especially leaf spot, pose a significant threat to mango production as they decrease the photosynthetic efficiency and overall yield of mango (Rani et al., 2020). Methods such as visual inspection and manual scoring that are commonly used for disease assessment in practice are subjective and characterized by heavy workload (Barbedo, 2013), which renders accurate disease assessment difficult but crucial for effective management. Mango leaf spot disease is caused by many fungal pathogens such as Pseudocercospora mangiferae and Colletotrichum gloeosporioides. These pathogens cause necrotic lesions that enlarge with time, resulting in leaf drop and reduced fruit yield (Kumar et al., 2019). Manual scoring approaches usually based on visual scoring systems (i.e., 0–5 or 0–9) according to lesion coverage. These methods have been shown to be limited as they suffer from observer bias, and lack reproducibility (Bock et al., 2010) and they are widely used. Many studies have investigated the application of meteorological data to develop disease prediction models to help with fungicide spray scheduling because disease infection and progression are strongly dependent on environmental conditions (Chen et al., 2020; Sanghavi et al. 2021).

Digital image processing has emerged as a powerful tool for plant disease detection. Techniques such as color space transformation, thresholding, and machine learning have been applied to crops including wheat, rice, and citrus (Barbedo 2016). Automated systems improve accuracy and efficiency, enabling large-scale disease monitoring. MATLAB provides extensive libraries for image preprocessing, segmentation, and feature extraction. Its flexibility allows researchers to design custom algorithms tailored to specific crops and diseases (MathWorks, 2022). Advances in digital image processing have enabled objective, reproducible, and automated disease quantification.

Plant disease detection has become a very strong tool from the field of digital image processing. Applications of techniques including color space transformation, thresholding, and machine learning have been realized across food crops such as wheat, rice and citrus (Barbedo, 2016). It offers a diverse range of tools for researchers to create their own specific algorithms for applicable crops and diseases (MathWorks, 2022). Digital Image Processing advancements allow objective, reproducible, and automated disease quantification. Images captured by drone (UAV) are also used for fast assessment of the damage caused by leaf spot diseases. A comparison of pros. and cons. in grading the damage by scanned images and drone acquired images are given in Table 1.

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**Table 1:** Comparison of quantification using scanned leaf images (flatbed scanner) vs. Drone (UAV)-based images

| Sr. no. | Aspects | Scanner acquired image damage quantification | Drone acquired image damage quantification |
|---|---|---|---|
| 1. | Scale of assessment | Leaf-level | Canopy/field-level |
| 2. | Nature of method | Destructive | Non-destructive |
| 3. | Indirect disease estimation | Disease severity is directly measured | . Disease severity is often inferred from canopy reflectance rather than direct lesion measurement. |
| 4. | Cost | Low cost | Very high cost |
| 5. | resolution for individual leaves | lesion-level quantification can be done with high accuracy | Fine lesion-level quantification is difficult, especially in dense canopies |
| 6. | Environmental dependency | It provides controlled imaging conditions including Uniform background, stable illumination, and fixed distance eliminate variability caused by shadows, sunlight, or viewing angle. | Image quality is affected by wind, cloud cover, sun angle, and atmospheric conditions. |

Images of scanned leaves are most suited for quantifying disease damage with high precision in a laboratory environment and for designing & validating the algorithms used by image analysis methods. In contrast, drone-based imaging is more suitable for large-area, non-invasive field monitoring and disease management. Even more robust framework for digital plant disease assessment would be a hybrid approach using scanner-based measurements to calibrate and validate UAV-derived indices.

Researchers can use computational methods to evaluate leaf images from drones in order to identify lesions, quantify damaged areas, and categorize the severity of the disease. For creating such applications, MATLAB's extensive image processing toolbox offers the perfect setting (Gonzalez and Woods, 2018). In order to automate the grading of leaf spot damage, this study presents a software system created especially for laboratory use that uses scanned images of mango leaves.

## MATERIALS AND METHODS

### Data Acquisition

A total of 45 mango leaves exhibiting varying degrees of leaf spot were collected from experimental orchards of ICAR-Central Institute for Subtropical Horticulture, Lucknow. These leaves were affected by different diseases such as anthracnose, red rust, phoma blight, bacterial canker, leaf gall, and powdery mildew.

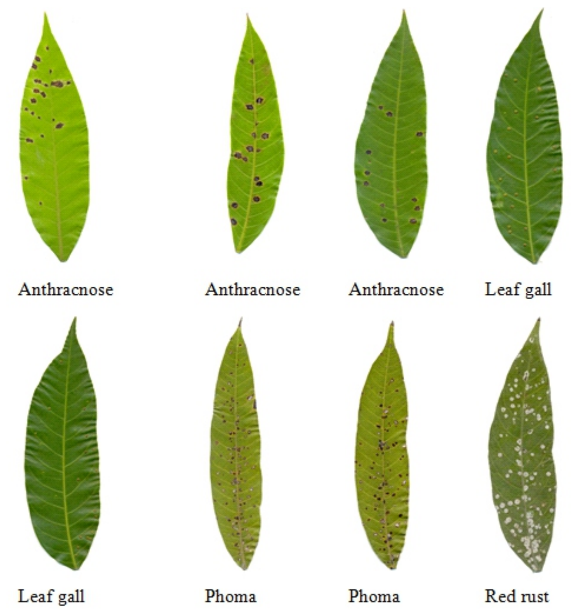


**Fig. 1:** Sample leaves damaged by leaf spot diseases of mango

Leaves were scanned using a flatbed scanner at 300 dpi to ensure high-resolution input images suitable for laboratory analysis in lossless tiff format (Fig. 2).

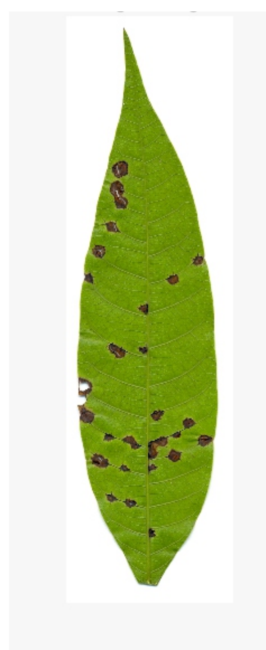

**Fig. 2:** Original RGB image affected by anthracnose

### Image Preprocessing

Some of important steps performed for image preprocessing are as given below:

- *Noise Reduction:* Median filtering was applied to remove scanning artifacts.
- *Color Space Conversion:* Images were converted from RGB to HSV to enhance lesion visibility. Following MATLAB command was used to convert an RGB image to HSV-

  $$HSV = rgb2hsv\ (I_{RGB})$$

- *Intensity Normalization:* Intensity normalization ensured consistent brightness across samples. Normalized intensity is calculated using equation (1)

$$I_{Norm} = \frac{I - I_{Min}}{I_{Max} + I_{Min}} \quad (1)$$

Where, Imin and Imax are minimum and maximum intensity values in the image.

The complete process of the proposed leaf disease severity grading system is shown in Figure 3.

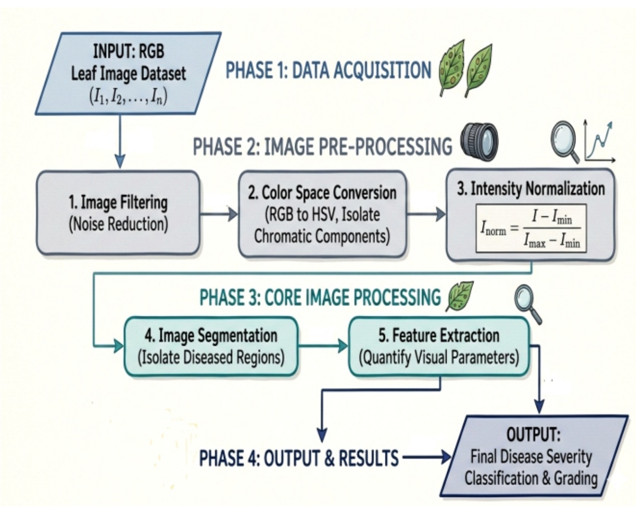


**Fig. 3:** Flowchart depicting the workflow of the proposed leaf disease severity grading system.

Fig. 3 clearly shows the steps of the suggested method for grading leaf disease damage. Filtering, color space conversion, and intensity normalization are all done to RGB leaf images before they are used. After the images have been processed, they are segmented to find the sick areas, and then features are extracted. Finally, the features that were taken out are used to grade and classify the severity of the disease.

### Image Segmentation

Complete leaf region is segmented to determine the leaf area (Fig. 4(A)). Thereafter, lesion regions were segmented using adaptive thresholding combined with morphological operations. The algorithm distinguished diseased tissue from healthy green areas (Fig. 4 (B).

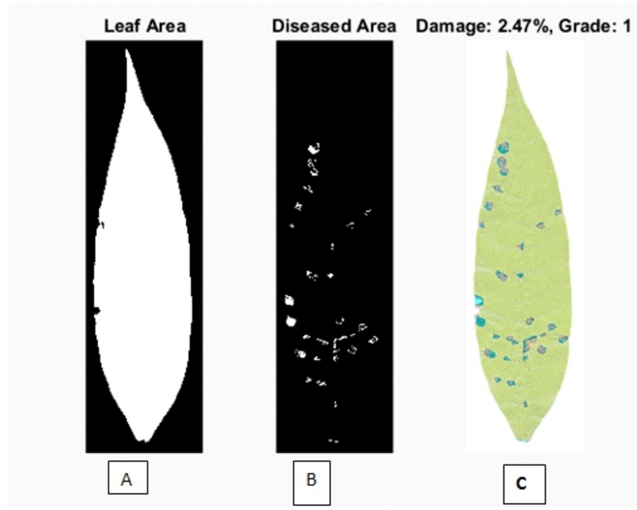


**Fig. 4:** Segmented areas (A) segmented leaf area (B) segmented lesion area (c) RGB damage image

After image is segmented, the features namely, damaged leaf area and complete leaf areas were extracted.

### Feature Extraction

Key features extracted included: Lesion area and leaf area (in pixels). Thereafter number of pixels is converted to the area in cm2 as follows:

### Leaf Area Calculation

The leaf area was calculated by counting the number of pixels within the leaf contours and converting this pixel count to real-world units based on a known scale (e.g., pixels per centimeter). The leaf area was calculated in centimetre square (cm2) using the resolution of the images. The term resolution is often used for a pixel count in digital imaging. Resolution of an image depends upon the size of the pixel. The smaller the size of the pixel, the higher the resolution will be and the clearer the object in the image will be. Images having smaller pixel sizes occupy more space on the disk. Resolution is expressed in Dots per Inch (DPI). After processing, the white pixels of an image, as shown in Fig. 4(A) were counted as Pixel count. 'Equation (2)' is used for calculation of leaf area.

$$Leaf\,Area(cm^2) = \left(\frac{Leaf\_Pixel_{count}}{dpi^2}\right) \times 6.4516(2)$$

Lesion Area Calculation

The lesion area is calculated by counting the white/ 'ON' pixel in lesion segmented image, for example Fig.4 (B) and by using equation (3)

$$LesionArea(cm^2) = \left(\frac{Lesion\_pixel_{count}}{dpi^2}\right) \times 6.4516(3)$$

### Percentage of damaged area calculation

It can be calculated by equation (4)

$$\text{Damaged leaf area (\%)} = \frac{\text{Lesion area}}{\text{Leaf area}} \times 100(4)$$

### Classification of disease severity

A rule-based classifier graded disease severity into ten categories (Bock et.al. 2010) (Table 2):

**Table 2:** Leaf damage (%) and corresponding grade

| SL | % damage | Grade |
|---|---|---|
| 1. | =0 | healthy |
| 2. | <=10 | 1 |
| 3. | <=20 | 2 |
| 4. | <=30 | 3 |
| 5. | <=40 | 4 |
| 6. | <=50 | 5 |
| 7. | <=60 | 6 |
| 8. | <=70 | 7 |
| 9. | <=80 | 8 |
| 10. | <=90 | 9 |
| 11. | >90 | 10 |

### Accuracies assessment

The coefficient of determination (R2) statistic provides information on a model's goodness of fit in statistical modelling. It indicates how closely the regression line resembles the actual data points in regression. The R2, which indicates the proportion of the dependent variable's change that can be anticipated from the independent variable or variables, would be the primary criterion for selecting the best-fit model. The five accuracy measurements described above can be calculated using the information below:

A. Coefficient of determination ($R^2$): $R^2$ is determined by creating a scatter plot, adding a linear trendline,

B. Accuracy rate (%): The accuracy rate was calculated by using the equation (5).

$$Accuracyrate = 100 - \frac{|(y_i - x_i|}{x_i} \times 100 (5)$$

Where xi and yi are the measured and calculated leaf length/width/AR for the ith leaf sample, respectively, and N is the number of samples.

C. Root mean square error (RMSE): It is computed by equation (6).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(x_i - y_i)^2}{N}} \quad (6)$$

Where, xi and yi are the measured and calculated leaf length/width/AR for the ith leaf sample, respectively, and N is the number of samples.

D. Mean absolute error (MAE): The formula for calculating the MAE is given in the equation (7).

$$MAE = \frac{\sum_{i=1}^{N} | y_i - x_i |}{N} (7)$$

E. Error rate (%): The error rate formula used is provided by Ali et al. (2012). It can be calculated using equation (8).

$$ErrorRate(\%) = \frac{|y_i - x_i|}{x_i} \times 100 (8)$$

To compare the estimate to a precise value, we calculated the error rate or percentage error was calculated. This percentage indicates the difference between the estimated and precise values as a portion of the exact value. This percentage error rate represents the difference, expressed as a percentage of the exact value, between the estimated and actual values.

## SOFTWARE IMPLEMENTATION

The software was developed in MATLAB with a graphical user interface (GUI) for ease of use. Users can load scanned images, run automated analysis, and export results in tabular format (MS® Excel file).

## RESULTS AND DISCUSSION

The software was tested on 24 scanned damaged mango leaf images. Digital images were processed in ImageJ software and % of leaf area damage by leaf spot diseases were determined and denoted as "Observed damage" The damage of the same leaves were graded by the software and denoted as "Calculated damage". Thereafter, accuracy of leaf damage assessed by software is assessed in comparison to the Observed leaf damage. Scatter chart of Figure 5, shows very good fit of observed leaf damage vs. calculated leaf damage with R2 =0.9976. The performance metrics included R2,mean accuracy(%), Mean error rate(%), Root Mean square error(RMSE), Mean absolute error(MAE)., and processing time are given in Table 3.

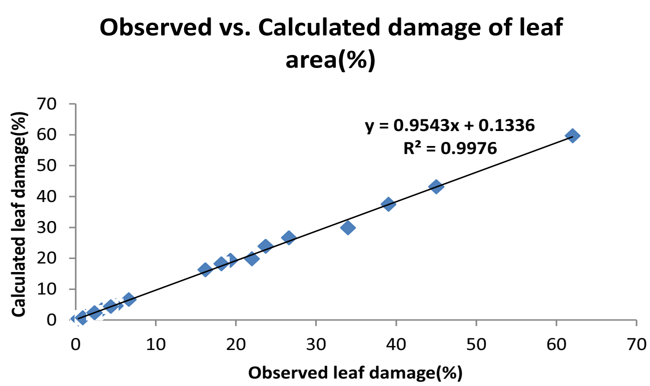


**Fig. 5:** Scatter plot between observed and calculated leaf damage (%).

**Table. 3:** Accuracy assessment between observed damage and calculated damage

| SN | Accuracy parameters | Value |
|---|---|---|
| 1. | R2 | 0.997 |
| 2. | RMSE | 1.260 |
| 3. | MAE | 0.619 |
| 4. | Mean error rate (%) | 3.390 |
| 5. | Mean accuracy rate (%) | 96.61 |
| 6. | Processing Time | Average of 2-3 seconds per image |

**Comparison of leaf spot damage assessed by human rater with QuickLeaf-LS software**

Coefficient of determination ($R^2$) and root mean square errors were assessed between the extent of damage by leaf spot disease graded but human rater and by the software by using 21 diseased leaf images.. The result revealed that QuickLeaf-LS software achieved a high level of accuracy in damage grading with RMSE =0.205, and moderate $R^2$ = 0.65. RMSE values indicate that there is good agreement between leaf damage graded by software and human rater (Fig.6).

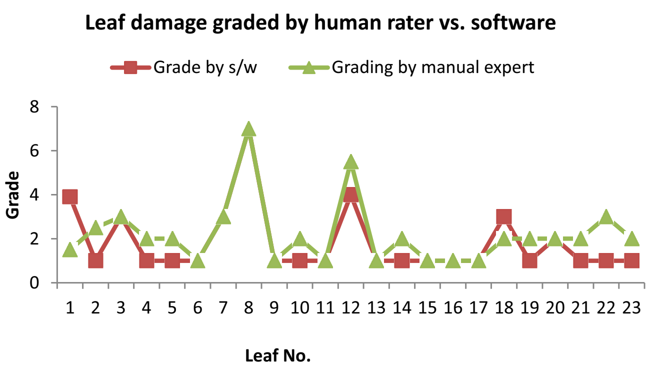


**Fig. 6:** Line chart showing leaf damage graded by software and human expert.

The system consistently identified lesions and quantified damage grade with minimal error. Misclassifications occurred primarily in cases of overlapping lesions or poor scan quality. Software processes images quickly with average processing time less than 4 seconds per image. This system based rapid analysis allows for timely assessment of disease severity.

Digital image processing is a reliable way to grade work instead of by hand. The high accuracy shows that MATLAB-based algorithms for finding lesions are very reliable. The GUI design makes it easy for lab technicians who don't know how to program to use it. Some of the problems are that it relies on high-quality scanned images and it can be hard to tell the difference between lesions that are close together. Future endeavours may incorporate machine learning classifiers to augment robustness and broaden applicability to field images obtained via smartphones.

## CONCLUSION

This study introduces an innovative software solution for the rapid, precise, and automated assessment of leaf spot damage in mango leaves through digital image processing. The system is implemented in MATLAB and works very well and accurately, making it a useful tool for plant pathology labs. The software helps with disease monitoring, breeding programmes and precision agriculture by making things less subjective and less work-intensive.

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