

An Automated Solution for Detecting *Polyalthia longifolia* Diseases from Images of Its Infected Leaves

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Abstract

Early detection of foliar diseases is essential for the health of *Polyalthia longifolia*. This article proposes an automated image analysis-based method for classifying leaves as healthy or infected. Texture parameters (Entropy, Contrast, Correlation, Energy, Homogeneity) and color parameters (R, G, B, ExG, ExR, VARI) are extracted for each leaf and then normalized to a healthy reference leaf. These parameters are combined into an overall score, calculated by Euclidean distance, which reflects the divergence from the healthy state. A unique decision curve with a threshold allows for the visual and quantitative differentiation of infected leaves from healthy leaves. The results show that healthy leaves have a score below the threshold, while infected leaves exceed it, with varying levels of severity. The percentages exceeding the threshold and the reliability estimates (80% to 98%) confirm the robustness of the approach. This solution provides a fast, accurate, and non-destructive tool for the automated diagnosis of diseases and paves the way for applications in large-scale monitoring and precision agriculture, enabling early and targeted intervention for the protection of *Polyalthia longifolia*.

Keywords

Foliar Disease, *Polyalthia longifolia*, Texture Parameters, Color, Overall Score

1. Introduction

Monitoring the phytosanitary status of plants is a major challenge for preserving

ecosystems and improving agricultural productivity [1]. *Polyalthia longifolia*, widely used for ornamental and medicinal purposes, is particularly vulnerable to various foliar diseases that can impair its growth, aesthetic appearance, and ecological value [2]. However, early detection of these diseases remains a significant challenge, as it most often relies on manual visual inspection, which is subjective, dependent on human expertise, and time-consuming [3]. Furthermore, the initial symptoms of foliar diseases can be subtle and difficult to perceive with the naked eye, which often delays phytosanitary interventions.

In this context, image and signal processing, combined with artificial intelligence and machine learning techniques, offers promising prospects for automating and improving the accuracy of plant disease diagnosis [4]. Analysis of digital leaf images makes it possible to extract discriminating features related to the color, texture, and spatial structure of plant tissues, which are strongly affected by the presence of diseases [5]. Commonly used techniques include RGB channel analysis, vegetation indices such as Excess Green (ExG), Excess Red (ExR), and VARI, as well as the extraction of texture descriptors based on the gray level co-occurrence matrix (GLCM), including entropy, contrast, correlation, energy, and homogeneity [6] [7].

These characteristics can then be exploited by various decision and classification models, such as metric distance-based methods, support vector machines (SVMs), artificial neural networks, random forests, or recent deep learning approaches using convolutional neural networks (CNNs) [8]. However, these complex models often require large annotated databases and significant computing resources, which limits their applicability in certain practical contexts [9].

In this context, lighter and more interpretable approaches, based on the fusion of features and similarity measures, constitute an interesting alternative. The combination of texture and color parameters in an overall score, calculated from normalized distances relative to a healthy reference state, makes it possible to quantitatively assess the degree of leaf infection while maintaining great simplicity of implementation and good robustness [10].

In this article, we propose an automated image and signal processing-based solution for detecting diseases in *Polyalthia longifolia* from images of infected leaves. The approach relies on extracting texture and color descriptors, normalizing them, and then integrating them into a global decision score, visualized using a single curve with a threshold that distinguishes healthy leaves from infected leaves and estimates the severity of the infection. The objective is to design an efficient, reproducible, and interpretable method that enables rapid and accurate identification of diseases, thus contributing to improved plant health management and the sustainable protection of this species.

This work is structured in three stages. First, we will present the adopted methodology, the tools used, and the steps involved in analyzing images of healthy and diseased leaves. The next stage is devoted to presenting the experimental results, followed by a discussion of the advantages and limitations of the identification

method implemented.

2. Materials and Methods

2.1. Materials

2.1.1. Image Acquisition Equipment

Images of *Polyalthia longifolia* leaves were captured using a digital imaging system comprising:

- A high-resolution digital camera, a latest-generation smartphone camera with a minimum resolution of 12 megapixels, to preserve the fine details of leaf symptoms.
- Uniform natural lighting to reduce shadows and variations in illumination.
- A plain background to facilitate leaf segmentation and limit interference from the background. The images were taken at a constant distance of 15 cm between the camera and the leaf, at a perpendicular angle to minimize geometric distortions [11].

2.1.2. Hardware Processing Platform

Image processing and analysis were performed on a computer platform with the following specifications:

- A computer equipped with an Intel(R) Core(TM) i3-6006U CPU @ 2.00 GHz.
- 4.00 GB of RAM for image processing.
- An SSD storage drive to accelerate data access.

This configuration provides a satisfactory balance between computing performance and hardware accessibility.

The following tools were used: a Windows operating system and a scientific development environment such as MATLAB 2016.

2.1.3. Plant Material and Dataset

The plant material used in this study consists of leaves of *Polyalthia longifolia* (family Annonaceae). The leaf images were acquired from *Polyalthia longifolia* plants at the University of Man, Côte d'Ivoire. The sampling includes both healthy leaves and leaves exhibiting pathological symptoms (**Figure 1**) such as necrotic spots, discoloration, chlorosis, and wilted areas.



Figure 1. Leaves infected with *Polyalthia longifolia*.

2.2. Method

After acquiring images of *Polyalthia longifolia* leaves, each sample was identified and classified according to its health status (healthy or infected), thus serving as a reference for evaluating the performance of the proposed detection system. We

preprocessed the images because they can contain variations in illumination, noise, and distortions related to the acquisition process, which could impair the extraction of relevant features [12]. These operations will therefore allow us to normalize the data, reduce noise, and highlight radiometric information directly related to the health status of the leaves. Image preprocessing is detailed in the following section.

2.2.1. Image Preprocessing

A digital image is a two-dimensional signal resulting from a physical acquisition process. The intensity observed at the pixel results from the interaction between illumination, leaf surface reflectance, and the camera's optical system. The recorded intensity is modeled by (1).

$$I(x, y, \lambda) = L(x, y, \lambda) \cdot R(x, y, \lambda) + n(x, y) \quad (1)$$

where $L(x, y, \lambda)$ represents the incident illumination, $R(x, y, \lambda)$ is the spectral reflectance of the leaf, λ is the wavelength, and $n(x, y)$ is the sensor noise.

This aims to attenuate the influence of L and n in order to highlight R , which is directly related to the leaf's health. We performed image dimensioning and discretization using formula (2).

$$I_r(u, v) = I\left(\frac{u}{s_x}, \frac{v}{s_y}\right) \quad (2)$$

Where s_x and s_y represent the spatial scaling factors along the horizontal and vertical directions.

The resizing is performed using bilinear interpolation, given by formula (3).

$$I_r(u, v) = \sum_{i=0}^1 \sum_{j=0}^1 w_{ij} I(x_i, y_j) \quad (3)$$

where w_{ij} are the interpolation weights associated with the four neighboring pixels (x_i, y_j)

To compensate for variations in illumination, we applied radiometric normalization to the image using formula (4):

$$I_n(x, y) = \frac{I_r(x, y) - I_{\min}}{I_{\max} - I_{\min}} \quad (4)$$

where $I_{\min}$ and $I_{\max}$ respectively denote the minimum and maximum intensities of the image. We also used statistical normalization via formula (5):

$$I_n(x, y) = \frac{I_r(x, y) - \mu_I}{\sigma_I} \quad (5)$$

where μ_I and σ_I are the mean and standard deviation of the light intensity. This operation homogenizes the image signal energy and improves the robustness of subsequent processing. We applied several filtering techniques, including Gaussian filtering (formula (6)) and median filtering (formula (7)), to reduce noise while progressively smoothing intensity variations, and also to suppress impulse noise

while preserving physical discontinuities, particularly the outlines of leaf lesions.

$$G_g(x, y) = \frac{1}{2\pi\sigma^2} \exp\left(-\frac{x^2 + y^2}{2\sigma^2}\right) \quad (6)$$

$$I_m(x, y) = \text{median}\{I_n(i, j)\}; (i, j) \in N(x, y) \quad (7)$$

where $N(x, y)$ denotes the neighborhood of the pixel (x, y) .

2.2.2. Leaf and Symptomatic-Region Segmentation

The segmentation aimed to isolate the region of high reflectance corresponding to the infected part of the leaf [13]. We determined the optimal threshold (Otsu threshold) by maximizing the inter-class variance, according to expression (8).

$$T^* = \arg \max_T \left[w_1(T) w_2(T) (\mu_1(T) - \mu_2(T))^2 \right] \quad (8)$$

where $w_i(T)$ denotes the probability of belonging to the class i and $\mu_i(T)$ represents the average of the class's gray levels. The method allows for automatic and robust separation between the healthy and diseased parts of the leaf.

We performed the segmentation using K-means clustering, minimizing the intra-class energy defined by relation (9).

$$E = \sum_{k=1}^k \sum_{x_i \in C_k} \|x_i - \mu_k\|^2 \quad (9)$$

where C_k is the set of pixels belonging to cluster k and μ_k corresponds to the center of cluster k . The final segmentation is obtained by applying the binary mask $M(x, y)$ to the filtered image, formula (10).

$$I_p(x, y) = I_m(x, y) \cdot M(x, y) \quad (10)$$

where $I_p(x, y)$ corresponds to the image of the segmented leaf.

The pre-processed image I_p constitutes a normalized, quasi-stationary and spatially coherent signal, thus promoting a robust and discriminating extraction of the characteristics associated with foliar diseases.

2.2.3. Feature Extraction

From the segmented leaf image $I_p(x, y)$ and its binary mask $M(x, y)$, we extracted features of color, texture, morphology, entropy, vegetation index, and deep features corresponding to the healthy and infected parts of the leaf image. We defined a feature vector $f = [f_c, f_t, f_m, f_e, f_v, f_d]$ that groups all the extracted features.

We described the color distributions using histograms in RGB and HSV color spaces with formula (11):

$$H_k(i) = \sum_{(x,y) \in \Omega} \delta(I_k(x, y) \in b_i); k \in \{R, G, B, H, S, V\} \quad (11)$$

where the dominant hue is given by the relation $H_{dom} = \arg \max_h p(h)$

Haralick descriptors and local binary models allowed us to calculate contrast, energy, homogeneity and correlation using formulas (12) and (13).

$$LBP(x, y) = \sum_{p=0}^{p-1} s(I_p - I_c) 2^p \quad (12)$$

$$GLCM(i, j) = \sum_{(x,y)} \delta(I(x, y) = i, I(x + \Delta x, y + \Delta y) = j) \quad (13)$$

We used entropy to measure the complexity and disorganization of intensities in infected areas from the thermal map of the leaf image [14]. Normalized vegetation indices allowed us to discriminate between healthy and infected areas by highlighting the degradation of chlorophyll activity (see formula (14)).

$$NDVI_{vis} = \frac{G - R}{G + R} \quad (14)$$

3. Results and Discussion

3.1. Parameter Results

Our method consists of building a model, but first, we sought to understand the relationship between the characteristics and the presence of disease. In order to obtain reliable and robust results, we resized and preprocessed the acquired leaf images. The leaves were segmented to separate infected areas from healthy areas. The results are shown in **Figure 2** and **Figure 3**.

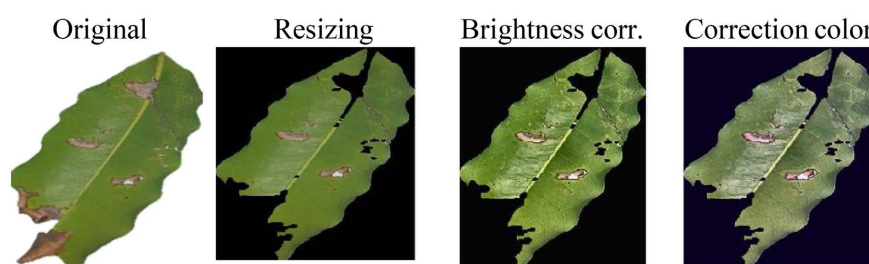


Figure 2. Image preprocessing and correction.

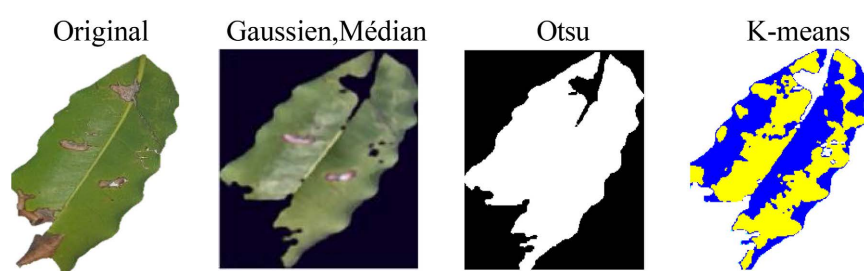


Figure 3. Image filtering and segmentation.

The results provided by the thermal map of the leaf image in **Figure 4** improve the separation of infected from healthy areas of the leaf. These results significantly enhance the discrimination between infected and healthy areas. The thermal representation highlights characteristic intensity contrasts and allows for the representation of local variations related to the physiological state of leaf tissues. Infected areas are distinguished by higher thermal values, thus facilitating their

identification and delimitation from healthy areas. This improved spatial separation contributes to more precise detection of affected regions, reducing the ambiguities observed with conventional segmentation methods based solely on visual information [15].

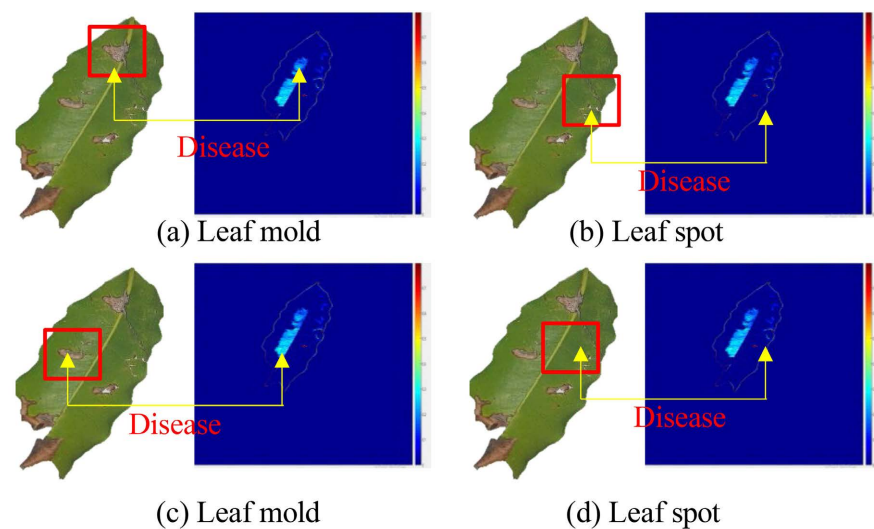


Figure 4. Thermal image map of the leaf of *Polyalthia longifolia*.

Table 1 presents the entropy values of healthy and diseased leaves and the average color of these regions. Diseased leaves exhibit higher average entropy and more or less pronounced average colors, reflecting an increase in textural complexity linked to the spread of the disease [16].

Table 1. Average entropy and color values of healthy and diseased leaves.

Leaf condition	Entropy	Average color		
		R	G	B
Healthy	1.4968	0.4791	0.8233	0.3714
M1	4.0102	0.7232	0.0112	0.0123
M2	5.0101	0.7112	0.0121	0.1021
M3	4.0002	0.6985	0.0211	0.1101

The histogram in **Figure 5**, obtained from **Table 1**, reveals a notable shift in distributions between healthy and diseased leaves. Infected leaves exhibit higher entropy values, with an average entropy of 4500 compared to that of healthy leaves around 1500, and a more spread-out distribution, indicating greater spatial heterogeneity induced by the disease. Diseased leaves show a marked decrease in the green (G) component and a relative increase in the red (R) and blue (B) components, reflecting chlorophyll degradation and an alteration in the physiological state of the leaf tissues. These results are confirmed by the work of [17].

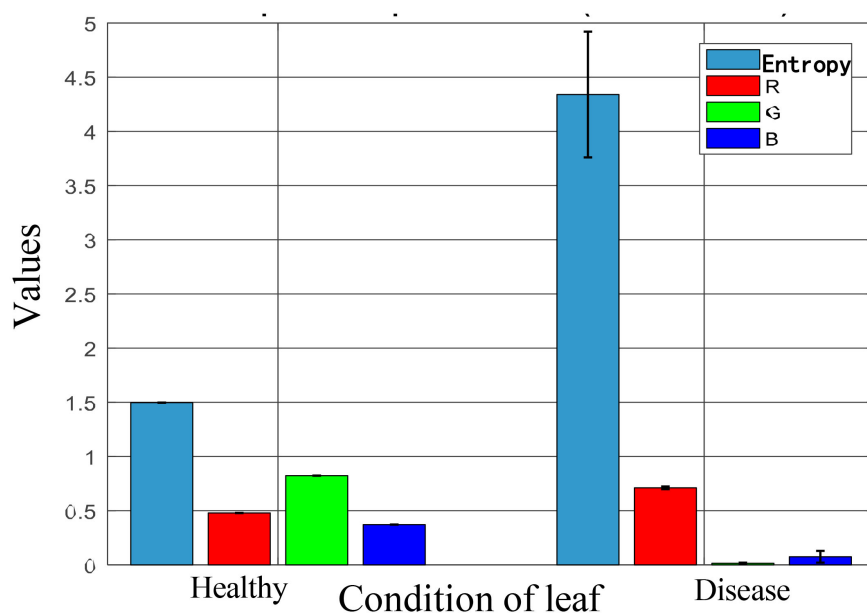


Figure 5. Entropy values and RGB components as a function of the leaf state.

Table 2. GLCM texture of healthy and infected leaf regions.

Leaf condition	GLCM Texture			
	Contrast	Correlation	Energy	Homogeneity
Healthy	0.1013	0.9840	0.3287	0.9606
M1	0.3012	0.1112	0.0023	0.0033
M2	0.4110	0.1101	0.0101	0.0002
M3	0.3210	0.1110	0.1000	0.0001

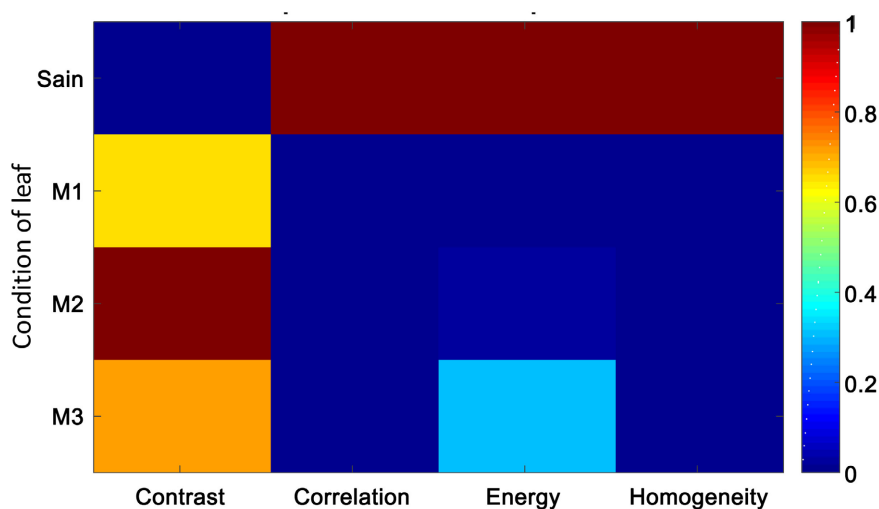


Figure 6. Normalized thermal map of GLCM parameters.

In **Table 2** and **Figure 6**, we can observe that diseased leaves exhibit significantly higher contrast values than healthy leaves, reflecting an increase in local

intensity variations due to the appearance of lesions and necrotic areas. A decrease in correlation is observed for infected leaves, indicating a loss of spatial dependence between pixels following leaf tissue degradation. Healthy leaves exhibit higher energy values, reflecting a homogeneous and regular texture, while diseased leaves show a decrease in this parameter due to the textural heterogeneity induced by the infection. A decrease in homogeneity is observed for infected leaves, reflecting an increased dispersion of gray levels caused by the presence of juxtaposed affected and healthy areas.

The normalized GLCM thermal map highlights a distinct textural signature between healthy and diseased leaves. Infected leaves show a marked increase in contrast, reflecting significant local variations related to the presence of lesions.

Conversely, the correlation, energy, and homogeneity parameters show significantly reduced values, indicating spatial disorganization and a loss of uniformity in leaf tissues. This overall picture confirms the significant impact of the disease on the textural structure of the leaves. The GLCM parameters are therefore highly reliable for discriminating between healthy and diseased leaves.

Table 3 shows that infected leaves exhibit a significant decrease in ExG and VARI indices, associated with an increase in the ExR index [18]. **Figure 7** highlights a distinct spectral signature between healthy and infected leaves. The healthy leaf shows high ExG values around 0.800 and VARI values around 0.700, associated with a low ExR value around 0.1500, reflecting vigorous growth and high chlorophyll activity.

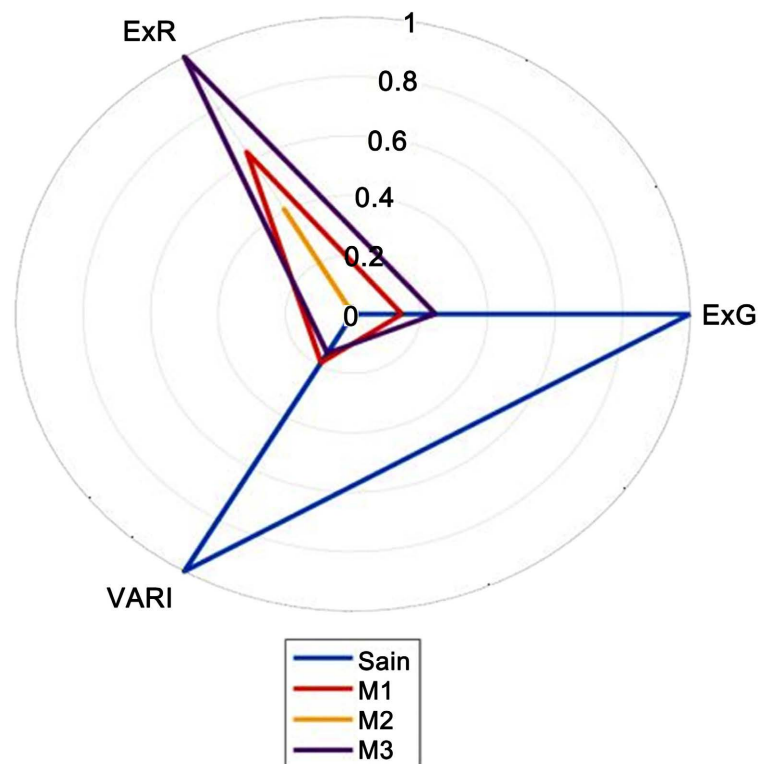


Figure 7. Radar diagram of vegetation indices.

Table 3. Vegetation indices of healthy and infected leaves.

Leaf condition	Vegetation indicator		
	ExG	ExR	VARI
Healthy	0.8049	0.1474	0.6947
M1	0.2120	0.4312	0.2312
M2	0.1111	0.3311	0.1233
M3	0.2811	0.5981	0.2101

In contrast, diseased leaves show an overall contraction of the polygon, characterized by a decrease in ExG and VARI and an increase in ExR, indicative of physiological stress and the degradation of plant pigments. A significant correlation is observed between vegetation indices and the proportion of infected areas. The decrease in index values is associated with an increase in the affected area, reflecting a progressive alteration of photosynthetic activity linked to the progression of the disease. This confirms the relevance of vegetation indices for discriminating the health status of these leaves [19].

3.2. Construction and Structure of the Database

The extracted textural, colorimetric, and spectral parameters were grouped into a feature database in **Table 4** to allow for the automatic identification of the leaf health status.

Table 4. Grouping of extracted parameter values.

Leaf	Entropy	Contrast	Correlation	Energy	Homogeneity	Class	
Healthy	1.4968	0.1013	0.9840	0.3287	0.9606	0	
M1	4.0102	0.3012	0.1112	0.0023	0.0033	1	
M2	5.0101	0.4110	0.1101	0.0101	0.0002	1	
M3	4.0002	0.3210	0.1110	0.1000	0.0001	1	
Leaf	R	G	B	ExG	ExR	VARI	Class
Healthy	0.4791	0.8233	0.3714	0.8049	0.1474	0.6947	0
M1	0.7232	0.0112	0.0123	0.2120	0.4312	0.2312	1
M2	0.7112	0.0121	0.1021	0.1111	0.3311	0.1233	1
M3	0.6985	0.0211	0.1101	0.2811	0.5981	0.2101	1

Data normalization was applied to ensure an equitable contribution from each parameter. The condition of the tested leaf was then determined by comparing its characteristics with those in the database, using a similarity measure based on Euclidean distance in **Figure 8**.

The database allowed us to identify the health status of four leaves, named F1, F2, F3, and F4.

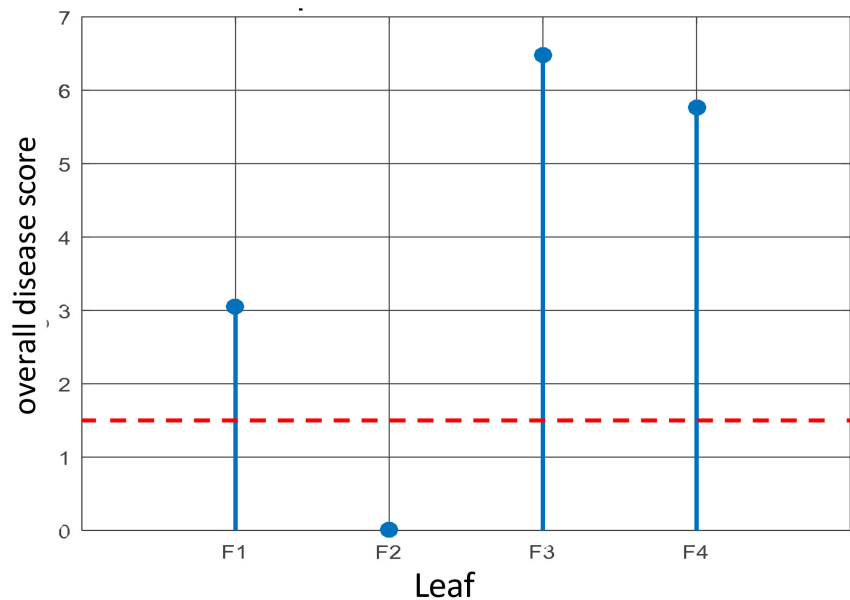


Figure 8. Single decision curve.

The single curve represents the overall score of each leaf, calculated from its texture and color characteristics, relative to a healthy reference leaf. The horizontal axis indicates the analyzed leaves (F1, F2, F3, F4), while the vertical axis shows the overall disease score. The horizontal red line represents the decision threshold for distinguishing healthy leaves from infected leaves. The analysis shows that F2 is well below the red line. Its distance from the threshold is approximately 90% below the threshold, indicating that this leaf is healthy, with a reliability of 95%. F1 slightly exceeds the threshold, at approximately 10% above it, indicating a mild or moderate infection, with a diagnostic reliability of approximately 80%. F3 is significantly above the red line, at more than 200% of the threshold, corresponding to a severe infection, with a very high reliability estimated at 98%. F4 is also above the threshold, at approximately 60% above the threshold, indicating moderate infection, with 90% reliability.

These results demonstrate that the approach combining texture parameters and color indices exhibits good discrimination capabilities [20]. Based on these results, it is possible to perform rapid and non-destructive monitoring of the health of *Polyalthia longifolia* leaves. This approach is particularly well-suited for large-scale diagnostics via image acquisition, as it reduces the need for time-consuming manual examinations. However, the diagnostic reliability depends on the choice of threshold due to the somewhat limited number of reference leaves. The analysis could be enhanced by incorporating more healthy reference leaves and leaves exhibiting various infections to calibrate the threshold more precisely.

4. Conclusions and Perspectives

This study presented an image-based approach for distinguishing healthy and symptomatic *Polyalthia longifolia* leaves using color and texture descriptors ex-

tracted from digital images. The proposed method combines selected RGB, texture, and vegetation-related features and summarizes their deviation from a healthy reference through a Euclidean-distance score.

The results obtained on the analyzed dataset indicate that the selected image descriptors can capture differences between visually healthy and symptomatic leaves. The decision-score representation also provides an interpretable way of visualizing the deviation of individual samples from the healthy reference state.

However, the present study should be considered a preliminary validation of the proposed image-analysis framework. The disease score represents similarity to a healthy reference and should not be interpreted as a calibrated probability of disease or as a direct measurement of disease severity. In addition, the identification of a specific causal pathogen cannot be established from image features alone and would require appropriate laboratory or molecular confirmation.

Further experiments should therefore include a larger and more diverse dataset covering multiple acquisition sessions, symptom types, and stages of disease development. The evaluation should use leaf-level or plant-level data partitioning to avoid information leakage and should include an independent held-out test set. Manually annotated lesion masks would also make it possible to evaluate the segmentation component independently using metrics such as intersection over union (IoU) and Dice coefficient.

Future work should additionally investigate threshold calibration under different acquisition conditions, comparison with supervised machine-learning classifiers, and validation against expert annotations and, where possible, laboratory-confirmed disease diagnoses. These experiments would provide a stronger basis for determining whether the proposed approach can be transferred from a controlled research setting to practical field-based plant health monitoring.

Author Contributions

All authors contributed to the conduct of this study and the preparation of the manuscript. All have approved the final version of the article.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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