

Article

Fractal-Based Image Analysis for Multi-Stage Detection of Tomato Late Blight Using a Laboratory Image Dataset of Greenhouse-Grown Tomato Plants

Fazliddin Makhmudov ¹, Jamshid Khamzaev ², Mirzaakbar Hudayberdiev ³, Baxodir Achilov ²,
Shavkat Otamurodov ⁴, Takhir Kuchkorov ⁵, Islambek Saymanov ^{6,7} and Alpamis Kutlimuratov ^{8,*}

¹ Department of Computer Engineering, Gachon University, Seongnam 13120, Republic of Korea; fazliddin12@gachon.ac.kr

² Department of Computer Systems, Tashkent University of Information Technologies Named After Muhammad Al-Kworazmiy, Tashkent 100084, Uzbekistan; hamzayevjf@gmail.com (J.K.); borya19861804@gmail.com (B.A.)

³ Department of Software of Information Technologies, Tashkent University of Information Technologies Named After Muhammad Al-Kworazmiy, Tashkent 100084, Uzbekistan; mirzaakbarhh@gmail.com

⁴ Department of Economics, Termez University of Economics and Service, Termez 190111, Uzbekistan; shavkat_otamurodov@tues.uz

⁵ Department of Digital Economy, Tashkent State University of Economics, Tashkent 100066, Uzbekistan; t.kuchkarov@tsue.uz

⁶ Department of Scientific Research, New Uzbekistan University, Mustaqillik Ave. 54, Tashkent 100007, Uzbekistan; i.saymanov@newuu.uz

⁷ Applied Mathematics and Intelligent Technologies Faculty, National University of Uzbekistan, Tashkent 100174, Uzbekistan

⁸ Department of Applied Informatics, Kimyo International University in Tashkent, Tashkent 100121, Uzbekistan

* Correspondence: kutlimuratov.aj@kiut.uz

Abstract

This paper considers the problem of early detection of late blight (*Phytophthora infestans*) in tomatoes based on computer vision and machine learning methods. The main purpose of the study was to develop a representative dataset of images of tomato leaves and an approach to extracting informative features for classifying the stages of disease development. A new dataset was generated using tomato plants grown under greenhouse conditions, with leaf images subsequently captured under controlled laboratory conditions, including five stages of late blight progression with variability in imaging devices, lighting conditions, and temporal disease dynamics. To improve the quality of image analysis, a preprocessing stage was applied, including conversion to grayscale, median filtering, and binarization using the Otsu method. In addition to the traditional textural features, fractal analysis was used to quantify the structural complexity of the affected leaf areas. To verify the information content of the selected features, classification experiments were conducted using Random Forest, XGBoost, and Support Vector Machine models, and the quality was evaluated using accuracy, precision, recall, and F1-score metrics. The results showed that the combination of textural and fractal features contributes to a more accurate distinction between the stages of disease. The developed dataset and the proposed approach can be used in further research on plant disease diagnosis, agricultural monitoring, and precision farming systems although it should be acknowledged that the dataset is limited to greenhouse settings, and field-scale generalizability requires further validation.

Keywords: late blight of tomatoes; image analysis; computer vision; fractal analysis; feature extraction; dataset; machine learning; *Solanum lycopersicum*



Received: 22 May 2026

Revised: 20 July 2026

Accepted: 5 August 2026

Published: 6 August 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and

conditions of the [Creative Commons](#)

[Attribution \(CC BY\)](#) license.

1. Introduction

Plant diseases are among the major threats to global food security, causing significant yield losses and economic damage worldwide. According to the Food and Agriculture Organization of the United Nations, plant pathogens considerably reduce agricultural productivity and pose a serious challenge to sustainable crop production [1]. In response to this growing threat, the development of automated disease diagnosis systems based on computer vision and artificial intelligence has emerged as an important research direction in precision agriculture, enabling early detection and timely intervention.

The relevance of such systems extends across diverse agricultural regions, including Central Asia, where crop production plays a critical role in food security and rural economies. In Uzbekistan, in particular, the problem of timely and accurate diagnosis of agricultural crop diseases has become increasingly critical in recent years. The country is characterized by a predominantly arid and hot climate; however, ongoing climate change has led to a steady increase in average annual temperatures and a growing frequency of extreme weather events, including heatwaves and irregular precipitation patterns [2,3]. These environmental shifts significantly affect agroecosystems by altering plant physiological processes and creating new favorable conditions for the emergence and spread of phytopathogens.

Although late blight (caused by *Phytophthora infestans*) is traditionally associated with high-humidity environments, microclimatic variations—particularly in greenhouse systems—can create localized conditions favorable for its development even in otherwise dry regions [4]. The increasing adoption of greenhouse cultivation in Uzbekistan further amplifies this risk, as controlled environments often involve fluctuating humidity and temperature levels that may inadvertently promote pathogen proliferation. Consequently, late blight remains one of the most economically significant diseases in tomato (*Solanum lycopersicum*) production, leading to substantial yield losses and reduced crop quality [5].

Despite extensive research in plant disease detection using computer vision and machine learning techniques, most existing studies primarily focus on binary classification tasks (i.e., “healthy” versus “diseased”). Such approaches fail to capture the progressive nature of plant diseases, particularly the intermediate stages that are crucial for early diagnosis and effective intervention. Furthermore, many datasets used in previous works are limited in size, lack class balance, and are often collected under controlled laboratory conditions using homogeneous imaging devices. This restricts the generalization capability of developed models and reduces their applicability in real-world agricultural settings.

In contrast, this study focuses on the development of a specialized dataset of tomato leaf images reflecting multiple stages of late blight progression. The dataset was acquired under greenhouse conditions using diverse imaging devices, thereby incorporating variability in resolution, lighting, and acquisition conditions. Such controlled diversity is intended to improve the robustness and practical relevance of the dataset within the scope of the experimental environment [5]. To further improve the discriminative power of the analysis, a feature extraction approach is proposed that combines conventional textural descriptors with fractal analysis. The latter enables quantitative characterization of the structural complexity of infected regions, providing additional insights into disease progression patterns that are not captured by traditional methods. It should be noted, however, that the current dataset is limited to greenhouse settings, and broader field-scale validation is planned as part of future work.

The scientific novelty of this work lies in the development of an image analysis technique for tomato leaves that explicitly accounts for the heterogeneity of input data caused by differences in optical characteristics of imaging devices, illumination conditions, and acquisition parameters. Furthermore, in contrast to conventional approaches that rely

primarily on standard texture descriptors, the proposed method integrates fractal analysis to quantify the structural complexity of affected regions. This allows for a more precise characterization of disease progression patterns and enhances the discriminative power of the extracted features.

The main objective of this study is to develop and validate an approach for the automatic identification of late blight stages in tomato plants based on leaf image analysis using computer vision and machine learning techniques. Particular emphasis is placed on ensuring the robustness of the approach under varying data acquisition conditions and improving its applicability in real agricultural environments.

To achieve this objective, the following tasks are addressed:

1. Dataset construction and structuring—collection and organization of tomato leaf images representing multiple stages of late blight under greenhouse conditions;
2. Image preprocessing—application of a preprocessing pipeline (including noise reduction, normalization, and segmentation) to ensure data consistency and improve analysis accuracy;
3. Feature extraction—extraction of informative descriptors based on fractal analysis and fractal dimension to capture the structural and textural properties of diseased regions;
4. Training sample formation—preparation of a machine learning-ready dataset through feature selection, labeling, and structuring of processed data for subsequent model development.

Overall, this study bridges the gap between controlled experimental datasets and real-world agricultural conditions by introducing a heterogeneous dataset and an enhanced feature extraction methodology. The integration of fractal analysis into the image processing pipeline offers new opportunities for capturing complex disease patterns. The proposed framework not only improves the understanding of late blight progression but also opens new directions for the development of adaptive and generalizable diagnostic systems in precision farming.

2. Related Works

Recent advances in deep learning have significantly improved the accuracy of plant disease diagnosis systems. Convolutional Neural Networks (CNNs), Vision Transformers (ViTs), and hybrid deep learning architectures have demonstrated excellent performance in tomato disease classification tasks. Murugesan et al. [1] proposed a hybrid deep learning framework combined with Grad-CAM explainability for robust crop disease classification. Xiang et al. [2] introduced DWTFormer, which integrates frequency-domain and spatial features for tomato disease recognition. Recent studies have also explored multi-modal learning [6], hybrid deep learning and fuzzy logic systems [7], transformer-based architectures [8], lightweight CNN models for edge devices [9,10], and enhanced CNN architectures incorporating attention mechanisms and residual connections [11–13]. These studies consistently demonstrate that deep learning approaches achieve high classification accuracy but often require large datasets, extensive computational resources, and limited model interpretability.

The quality and diversity of image datasets play a crucial role in developing reliable disease diagnosis systems. Existing tomato disease datasets are often collected under controlled laboratory conditions and mainly focus on disease identification rather than disease progression analysis. Publicly available datasets typically contain limited information regarding temporal disease development and severity levels [5]. Recent studies have increasingly emphasized disease severity estimation and multi-stage classification [6,11,14]. However, most datasets remain restricted to disease presence detection and do not explicitly represent multiple stages of late blight progression under varying acquisition

conditions. Therefore, the development of datasets containing heterogeneous imaging devices, varying illumination conditions, and disease progression stages remains an important research challenge.

Besides deep learning methods, feature engineering techniques remain important for interpretable disease analysis. Texture descriptors such as Haralick features continue to be widely used in agricultural image processing [15]. Fractal analysis has attracted increasing attention due to its ability to characterize structural complexity and irregular biological patterns. Nurmukhamedov et al. [16] investigated fractal image processing techniques, while Das and Mohanta [17] demonstrated the usefulness of textural fractals in analyzing natural biological structures. Recent studies on plant disease classification have shown that fractal dimensions can provide valuable information about complex image structures and may complement conventional texture descriptors [18]. Nevertheless, the application of fractal analysis for multi-stage tomato late blight classification remains insufficiently explored.

To address these limitations, this study introduces a heterogeneous greenhouse dataset containing five stages of tomato late blight progression and proposes a feature extraction framework that combines texture descriptors with fractal analysis. Unlike conventional disease recognition approaches, the proposed methodology focuses on disease severity progression and interpretable feature representation suitable for machine learning-based classification.

An analysis of existing publications shows that most studies either do not consider the process of forming datasets of plant images or use datasets limited in diversity and shooting conditions.

Comparison with Existing Datasets and Novelty

Unlike existing datasets of images of tomato diseases, the proposed dataset contains images obtained using various devices (smartphones and digital cameras), takes into account the variability of lighting conditions and includes five stages of late blight development. Additionally, the dataset reflects the temporal dynamics of the disease. These features make it possible to bring the data closer to the real conditions of agriculture and increase the stability of machine learning models.

Table 1 shows that existing datasets on tomato diseases are typically collected under controlled conditions and do not reflect disease progression over time. In contrast, the proposed dataset includes five annotated stages of late blight, heterogeneous imaging devices, different lighting conditions, and the progression of disease symptoms over time. These characteristics enhance the representativeness of the dataset for real-world agricultural scenarios and provide the basis for more reliable machine learning models.

Table 1. Comparing tomato disease image datasets.

Dataset ¹	Images	Disease Stages	Multi-Device	Different Lighting	Time Processing ²
PlantVillage	14,531	No	No	No	No
Taiwan Tomato Dataset	622 (4976 augmented)	No	No	Partial	No
Greenhouse Tomato	1026	Partial	No	No	No
Proposed dataset	5245	Yes (5 stage)	Yes	Yes	Yes

Note: ¹ PlantVillage: Hughes, D.P.; Salathé, M. An open access repository of images on plant health to enable the development of mobile disease diagnostics through machine learning and crowdsourcing. arXiv:1511.08060, 2015. Taiwan Tomato Dataset: Huang, M.-L.; Chang, Y.-H. Dataset of Tomato Leaves. Mendeley Data, 2020, <https://doi.org/10.17632/ngdgg79rzb.1>. ² "Time processing" refers to whether the dataset captures the temporal progression of disease symptoms through repeated image acquisition of the same plant/leaf over time, rather than single-time point snapshots.

Unlike PlantVillage and similar datasets, which mainly focus on disease category recognition, the proposed dataset highlights the gradual development of late blight and

takes into account the variability of data collection conditions. Thus, the novelty of this work lies not only in the construction of a dataset, but also in the integration of temporal disease progression with fractal-based feature extraction.

3. Materials and Methods

In addition to the traditional features of computer vision, fractal analysis is used in the work, which makes it possible to quantify the complexity and heterogeneity of the texture of the affected areas of the leaf [6]. The fractal dimension serves as an informative feature reflecting the degree of structural changes caused by the development of late blight. The workflow of the proposed approach is shown in Figure 1 of the dataset formation and processing process.

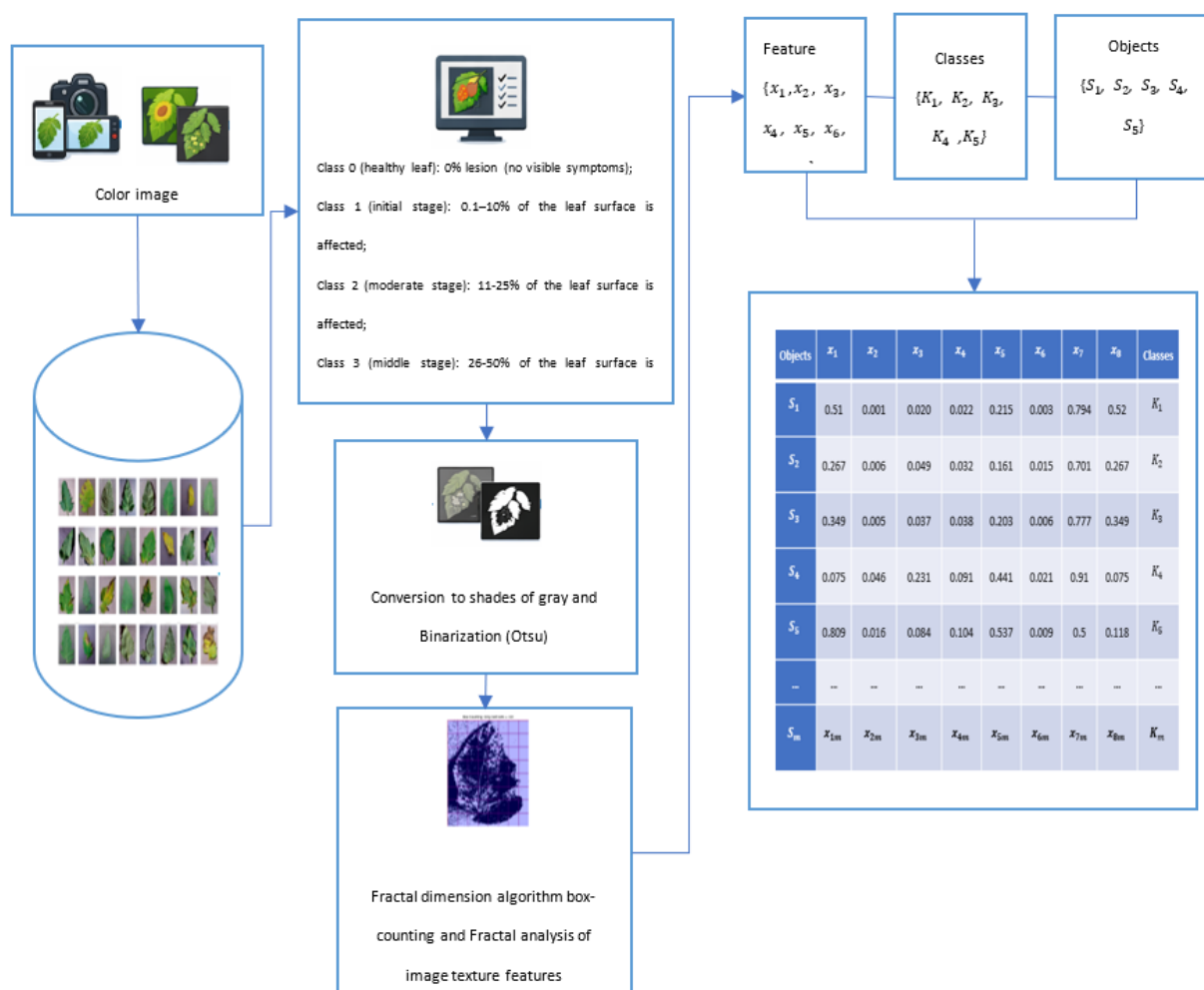


Figure 1. General workflow of the proposed tomato late blight diagnosis system, including image acquisition, preprocessing, lesion segmentation, extraction of texture and fractal features, formation of the training dataset, and machine learning-based classification of disease stages.

As shown in Figure 1, the proposed approach includes the stages of image collection, marking up the stages of the disease, preprocessing (conversion to grayscale and binarization by the Otsu method), extracting informative features based on fractal analysis, as well as forming a final dataset. Such a structured scheme improves the quality of data and increases the effectiveness of subsequent application of machine learning methods.

3.1. Formation and Structuring of a Dataset of Images of Tomato Leaves

The study used both mobile devices (including modern high-resolution smartphones) and digital cameras. This made it possible to form a heterogeneous dataset that reflects the real shooting conditions and ensures the stability of the developed algorithms to differences in hardware characteristics [7].

The devices and shooting parameters shown in Table 2 reflect a variety of image acquisition conditions, including differences in sensor types, lighting, and distance to the subject. Experimental studies were conducted in laboratory conditions using specialized equipment and a greenhouse setup.

Table 2. Device characteristics and conditions for taking images of tomato leaves ¹.

NO	Device Type	Device Model	Focal Length	Lighting	Distance to the Object	Shooting Conditions
1	Smartphone	Samsung Galaxy S22 Ultra	23 mm	Natural (indoor)	20–30 cm	Handheld shooting
2	Smartphone	Redmagic 11 Pro	24 mm	Mixed	25–35 cm	Handheld shooting
3	Digital camera	Canon EOS Lite	35 mm	Artificial LED	20–30 cm	Tripod
4	Digital camera	Nikon D3500	50 mm	Natural (indoor)	20–30 cm	Tripod

¹ All devices used a complementary metal-oxide semiconductor (CMOS) image sensor.

Description Dataset Structure

To form the dataset, tomato plants were cultivated under greenhouse conditions and subsequently inoculated with a sporangial suspension of *Phytophthora infestans* at a concentration of approximately 2×10^4 sporangia/mL, applied to the leaf surface using a hand-held sprayer. Leaf samples were collected every 2–4 days as the disease progressed and photographed under controlled laboratory conditions using different imaging devices. Disease severity was assessed by an expert in plant pathology based on the visually affected leaf area. As a result, five disease classes were defined, representing the progression from healthy leaves to severe infection. The final dataset consisted of 5245 images, all acquired under controlled laboratory conditions from leaves collected from green-house-grown tomato plants. This acquisition protocol allowed gradual morphological and textural changes to be recorded throughout disease development. Each image in the dataset was annotated by an expert in agronomy and phytopathology. The generated dataset was also used in our previous work [19] for image analysis and classification. The classification was performed based on the percentage of the visibly affected leaf surface. Five classes of the degree of the disease were identified:

1. Class 0 (healthy leaf): 0% lesion (no visible symptoms); 1000 images.
2. Class 1 (initial stage): 0.1–10% of the leaf surface is affected; 1100 images.
3. Class 2 (moderate stage): 11–25% of the leaf surface is affected; 1050 images.
4. Class 3 (middle stage): 26–50% of the leaf surface is affected; 1000 images.
5. Class 4 (severe stage): $\geq 51\%$ of the leaf surface, accompanied by significant damage; 1095 images.

Figure 2 shows examples of images of tomato leaves, showing both healthy and blight-affected areas at various stages of the disease. The variability of color, textural and structural characteristics is observed, which necessitates the use of computer vision methods for their automatic analysis and classification [8]. Tomato plants were artificially infected in greenhouse conditions. The pictures were taken every 2–4 days. The expert agronomist commented on the stages of the disease based on the percentage of the affected leaf area. Each image was analyzed independently and assigned to one of the five severity classes of the disease.

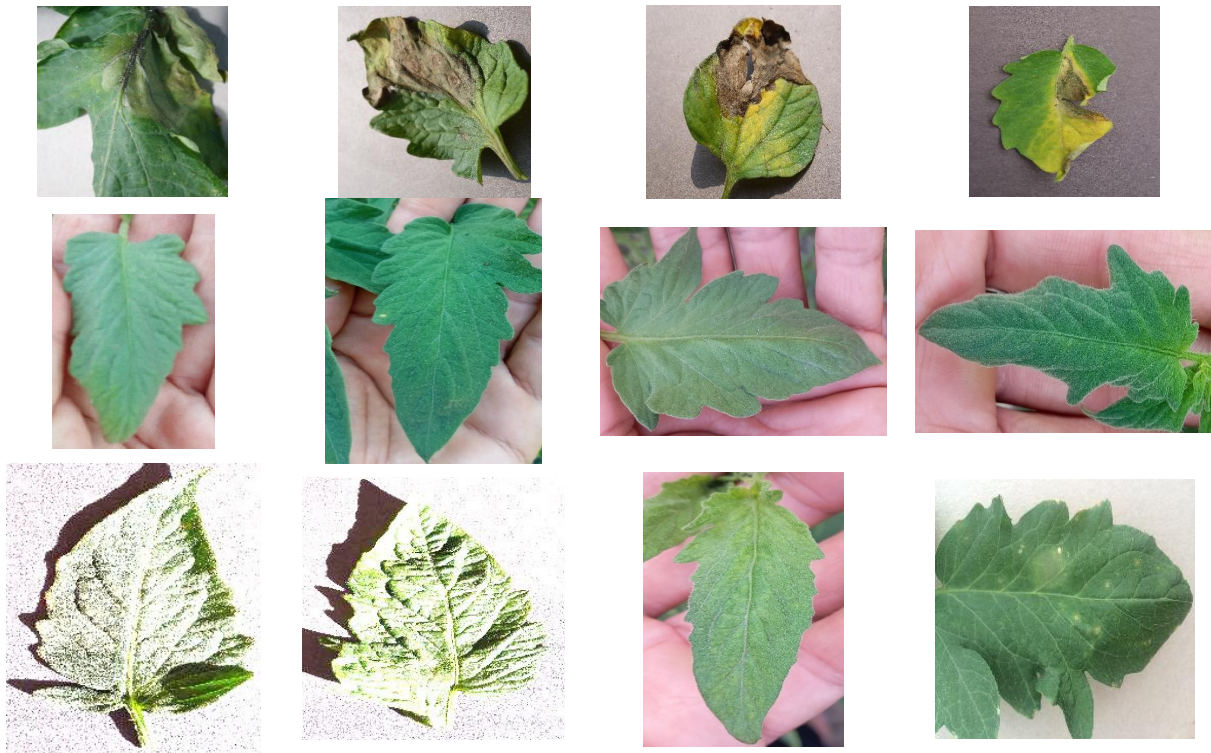


Figure 2. Representative examples of tomato leaf images included in the dataset, illustrating different stages of late blight progression, from healthy leaves to severe infection. Variations in lesion morphology, texture heterogeneity, and affected area structure can be observed across disease stages.

3.2. Preprocessing of Images

To improve image quality and ensure reliable extraction of lesion-related features, all tomato leaf images were converted to grayscale and processed using median filtering for noise suppression. Grayscale conversion reduced computational complexity while preserving structural information required for subsequent texture and fractal analysis. Median filtering was applied to suppress impulsive noise while preserving lesion boundaries and contour structures important for feature extraction [15]:

Binarization by Otsu's Method

Otsu's method automatically selects a threshold t that separates an image into two classes [20]:

- ✓ Class 1 (background): pixels with intensity $I \leq t$;
- ✓ Class 2 (object): pixels with intensity $I > t$.

For the selected threshold t , the binarized image $B(x, y)$ is determined by the rule:

$$B(x, y) = \begin{cases} 1, & I(x, y) \leq t \\ 0, & I(x, y) > t \end{cases} \quad (1)$$

For tomato late blight images, diseased regions generally correspond to darker intensity values after grayscale conversion. Therefore, affected areas are assigned to the foreground class (object), while healthy tissues and background regions belong to the complementary class. Although diseased regions generally exhibit lower intensity values after grayscale conversion, shadows, illumination variations, and background artifacts may produce similar intensity patterns. Therefore, Otsu thresholding should be considered as an approximate segmentation technique rather than a definitive lesion detector.

A normalized brightness histogram is used:

$$P(i) = \frac{h(i)}{N}, i = 0, 1, \dots, L - 1 \quad (2)$$

For any fixed threshold t , the image is divided into two groups, and the probabilities of the group are entered:

$$\begin{cases} w_1(t) = \sum_{i=0}^t P(i) \\ w_2(t) = \sum_{i=t+1}^{L-1} P(i) \end{cases} \quad (3)$$

Average class brightness:

$$\begin{cases} \mu_1(t) = \frac{\sum_{i=0}^t iP(i)}{w_1(t)} \\ \mu_2(t) = \frac{\sum_{i=t+1}^{L-1} iP(i)}{w_2(t)} \end{cases} \quad (4)$$

The criterion of optimality:

$$\sigma_b^2(t) = w_1(t) (\mu_1(t) - \mu_T)^2 + w_2(t) (\mu_2(t) - \mu_T)^2 \quad (5)$$

The threshold is chosen so that the intergroup variance is maximal [21]:

$$t_1 = \arg \max_{0 \leq t \leq L-1} \sigma_b^2(t) \quad (6)$$

The Otsu method automatically selects the global binarization threshold by maximizing the intergroup variance, which makes it possible to steadily separate the affected areas of the leaf from the background without manually adjusting the parameters.

3.3. Extraction of Informative Features Based on Fractal Analysis of Textural Features and Fractal Dimension

3.3.1. Rationale for Fractal Analysis

Late blight manifests itself in the form of complex and irregular patterns on the surface of tomato leaves. Traditional feature extraction methods, such as color histograms and texture descriptors (for example, GLCM) primarily capture local or statistical properties of an image. However, they do not adequately describe the geometric complexity and unevenness of the affected areas. Fractal analysis, in particular the cell-by-cell method, allows us to obtain a multiscale characterization of structural complexity. It is resistant to noise and is able to detect irregular biological patterns.

Thus, fractal characteristics provide more informative descriptors for modeling disease progression compared to traditional methods.

3.3.2. Fractal Dimension Algorithm Box-Counting

For quantification of the geometric complexity and unevenness of the affected areas, the image is covered with a grid of $\varepsilon \times \varepsilon$ and the number of occupied cells is calculated. $\varepsilon \times \varepsilon$ is a discrete approximation of the metric coverage of the set [16].

$$N(\varepsilon) = \sum_{i=1}^{M(\varepsilon)} I_i(\varepsilon) \quad (7)$$

where ε is the grid cell size, $N(\varepsilon)$ is the number of occupied grid cells containing lesion pixels, $M(\varepsilon)$ is the total number of grid cells, $I_i(\varepsilon)$ is whether the cell is occupied the occupied cell corresponds to a grid region containing at least one foreground pixel of the segmented lesion.

Fractal dimension is calculated as

$$D = -\lim_{\varepsilon \rightarrow 0} \frac{\ln N(\varepsilon)}{\ln \frac{1}{\varepsilon}} \quad (8)$$

where D is the estimated fractal dimension; higher values of D correspond to increased structural complexity and irregularity of diseased regions.

- $D \approx 1$ —smooth shape;
- $D \in [1.6, 2]$ —biologically complex structures (spots of disease).

Thus, the use of fractal analysis based on the box-counting method provides a quantitative assessment of the geometric complexity of the affected leaf areas, which contributes to increasing the information content of the feature space and improving the accuracy of models for classifying the stages of late blight.

This approach allows for effective consideration of the geometric complexity of the affected areas and the use of the obtained characteristics for the subsequent classification of the stages of late blight (Figure 3).

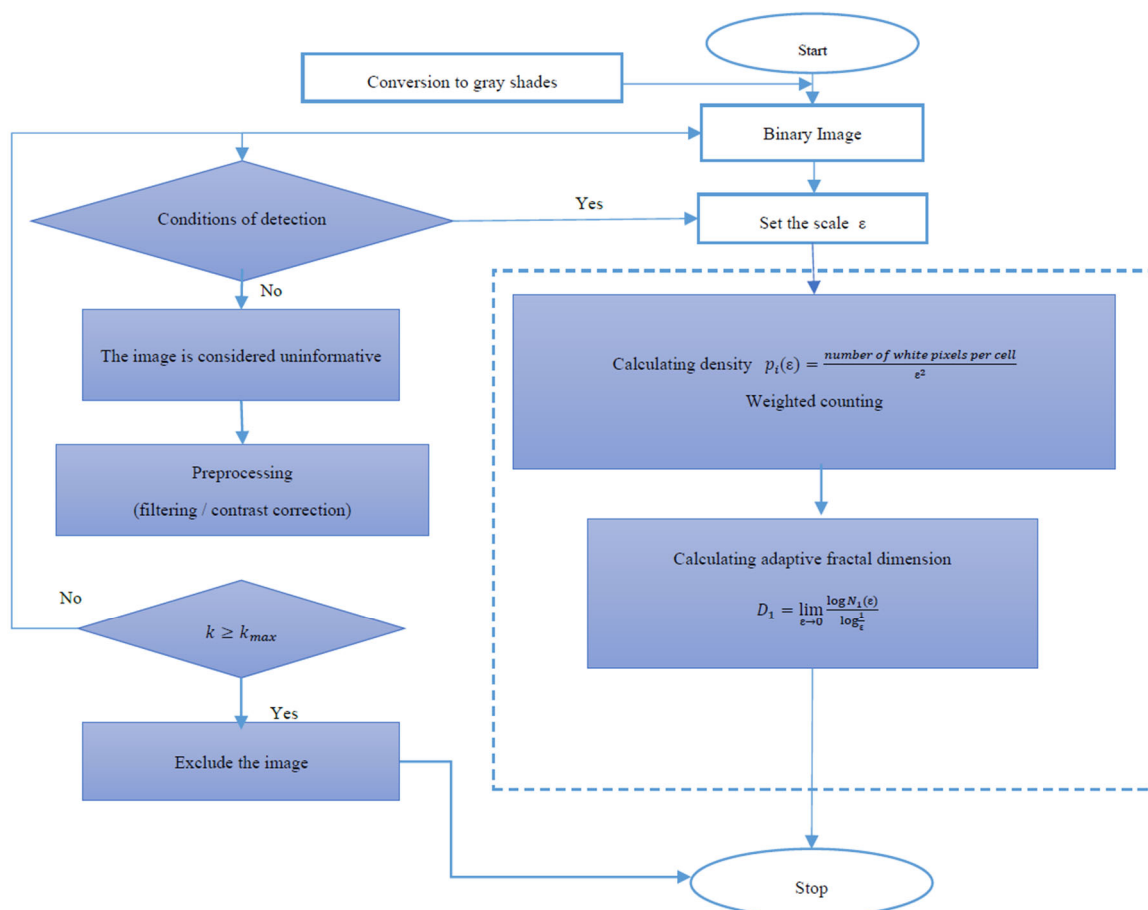


Figure 3. Block diagram of the proposed fractal analysis procedure used for characterization of tomato leaf lesions. The algorithm includes image preprocessing, lesion segmentation using Otsu thresholding, grid generation for box-counting analysis, estimation of fractal dimension, and formation of informative fractal descriptors.

3.3.3. Fractal Analysis of Image Texture Features

Fractal analysis of image texture features is implemented as a sequential algorithm that includes seven main stages of processing and calculations [17].

Step 1. Image Contrast

Evaluates brightness variability [22]:

$$\sigma_I = \sqrt{\frac{1}{n} \sum_{i=1}^k (I_i - \bar{I})^2 n_i} \quad (9)$$

I_i is the pixel brightness, $\bar{I}$ is the average brightness. Selection of informative image features and suppression of noisy data.

Step 2. Number of contours

The number of closed objects in a binarized image is calculated [23]:

$$L = |\{C_i | i = 1, 2, \dots, n\}| \quad (10)$$

Interpretation: if $L = 1$, there is one object (e.g., one leaf). If $L = 10$, there are ten separate spots or objects in the image. If $L = 0$, no contours are detected, indicating that the image is either too blurred or completely white or black.

Step 3. Average area of contours

Area of a single contour (Gauss's formula) [18]:

$$A_i = \frac{1}{2} \left| \sum_{j=1}^k (x_j y_{(j+1)} - x_{(j+1)} y_j) \right| \quad (11)$$

k is the number of points in the contours, $(x_{i(k+1)} = x_{i1}, y_{i(k+1)} = y_{i1})$ is the closed contour. The average area of all contours is calculated if n contours are found:

$$\bar{A} = \frac{1}{n} \sum_{i=1}^n A_i \quad (12)$$

This feature reflects the average size of lesion regions and helps reduce the influence of small isolated artifacts and noise generated during image segmentation.

Step 4. Standard deviation of the contour area

$$\sigma_P = \sqrt{\frac{1}{n} \sum_{i=1}^n (P_i - \mu_P)^2} \quad (13)$$

P_i is the perimeter of the i -th contour, μ_P is the average perimeter $(\mu_P = \frac{1}{n} \sum_{i=1}^n P_i)$. If the spread of values is large, the spots on the leaves have different shapes [24].

Step 5. Average perimeter of contours

The perimeter of a single contour [14]:

$$P_n = \sum_{j=1}^n \sqrt{(x_{j+1} - x_j)^2 + (y_{j+1} - y_j)^2} \quad (14)$$

P_k is the length of the boundary of the j -th contour, and n is the number of contours. The average perimeter:

$$\bar{P} = \frac{1}{n} \sum_{i=1}^n P_n \quad (15)$$

reflects the complexity of the shape of the lesion boundaries.

Step 6. Asymmetry

Geometric shape asymmetry [25]:

$$S = \frac{\frac{1}{n} \sum_{i=1}^n (x_i - m)^3}{L^3} \quad (16)$$

x_i is the pixel brightness value, L is the standard deviation, and m is the sample mean.

- $S \approx 0$ —the distribution is symmetric (for example, close to normal).
- $S > 0$ —right asymmetry (long tail to the right, more large values).
- $S < 0$ —left asymmetry (long tail to the left, more small values).

Step 7. Entropy descriptor

Characterize the degree of “complexity” of the form [11]:

$$E = -\sum_{i=1}^n P_i \log_2 P_i \quad (17)$$

where P_i is the fraction of pixels in the i -th brightness level, and the logarithm is base 2 $\Rightarrow E$ is measured in bits. More severely infected regions generally exhibit higher entropy values due to increased texture heterogeneity and structural complexity of the lesions.

As shown in Figure 4, the algorithm includes preprocessing stages, image information assessment, and calculation of texture and fractal characteristics, such as contrast, number of contours, area, perimeter, and entropy descriptors. The obtained features form a feature vector used in the subsequent stages of classification of stages of late blight.

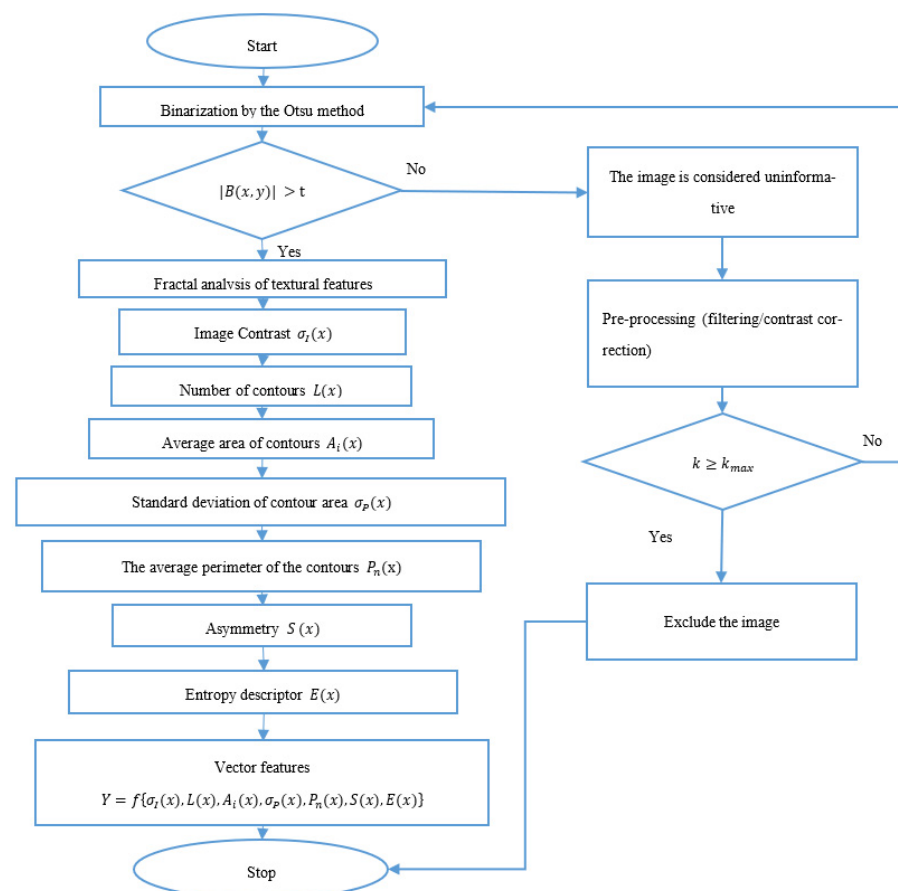


Figure 4. Flowchart of the proposed feature extraction framework for tomato leaf analysis. The algorithm includes preprocessing, image informativeness evaluation, Otsu-based lesion segmentation, extraction of texture descriptors (contrast, contour statistics, entropy, asymmetry), and estimation of fractal dimension for formation of the final feature vector used in disease stage classification.

3.4. Formation of a Training Sample Based on Processed Images and Selected Features

To formalize the process of classifying the stages of late blight, a set of informative features was formed, and the corresponding objects and classes were defined to reflect the degree of leaf surface damage.

As shown in Table 3, the generated feature vector includes textural and structural characteristics of images, such as contrast, number of contours, geometric parameters, and entropy descriptors. The correspondence of features to disease classes allows them to be used as input parameters for building and training classification models.

Table 3. Description of features, objects, and classes for classifying stages of tomato late blight.

Signs	Objects	Classes
x_1 = Contrast	S_1 = healthy leaves	K_1 = 0–0% infection
x_2 = Number of contours	S_2 = Stage 1 of the disease	K_2 = 1–0.1–10% infection
x_3 = Average area of contours	S_3 = Stage 2 of the disease	K_3 = 2–11–25% infection
x_4 = Standard deviation of area of contours	S_4 = Stage 3 of the disease	K_4 = 3–26–50% infection
x_5 = Average perimeter of contours	S_5 = Stage 4 of the disease	K_5 = 4–51 + % infection
x_6 = Asymmetric descriptor		
x_7 = Entropy descriptor		
x_8 = Fractal dimension		

Normalization Method

The paper uses linear normalization (Min–Max Scaling), which converts the values of each feature x to the range [0,1] using the formula [12]:

$$X'_i = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}} \quad (18)$$

where X_i is the initial value, $X_{\min}$ is the minimum value of the column, $X_{\max}$ is the maximum value of the column.

The use of Min–Max normalization is a critical step in data preprocessing, as it ensures that features are brought to a uniform scale, eliminates the imbalance of value ranges, and improves the convergence of learning algorithms. In addition, normalization increases the numerical stability of machine learning models and prevents the dominance of features with large values in the optimization process.

4. Results

4.1. Performing Image Preprocessing

A sequence of image preprocessing methods was applied to select the affected areas of the leaf, including grayscale conversion, median filtering, and Otsu binarization.

As shown in Figure 5, the use of these methods allows for effective noise suppression and the identification of affected areas, ensuring proper data preparation for subsequent analysis and feature extraction.

4.2. Extraction of Informative Features Based on Fractal Analysis of Textural Features and Fractal Dimension

The box-counting method was used to estimate the fractal dimension of the affected areas of the leaf, using different grid scales.

As shown in Figure 6, changing the size of the grid cells affects the number of occupied areas, which allows us to determine the relationship and calculate the fractal dimension, which characterizes the complexity of the structure of the affected areas. To calculate the fractal dimension, we plotted the relationship between the logarithm of the number of occupied cells and the logarithm of the inverse cell size. Linear regression of the box-

counting data produced an estimated fractal dimension of $D = 1.85$ with an excellent goodness of fit ($R^2 = 0.998$, $p < 0.001$).



Figure 5. Sequential preprocessing stages applied to tomato leaf images for late blight analysis, including the original RGB image, grayscale conversion, median filtering for noise suppression, and Otsu threshold-based binarization for segmentation of diseased regions.

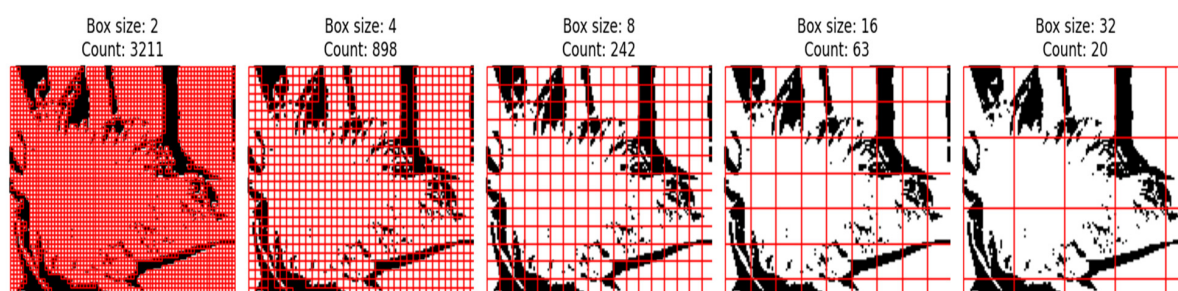


Figure 6. Application of the box-counting method for estimation of fractal dimension in tomato leaf lesions using different grid scales. The figure demonstrates how the number of occupied cells changes with cell size during analysis of lesion structural complexity.

4.3. Fractal Analysis of Image Texture Features

Textural, geometric, and fractal characteristics of the images were calculated to analyze the information content of the features and evaluate their contribution to describing the leaf state.

As shown in Figure 7, the extracted features allow us to quantify the image structure, including the complexity of the contours and the degree of texture heterogeneity, which forms the basis for constructing an informative feature vector.

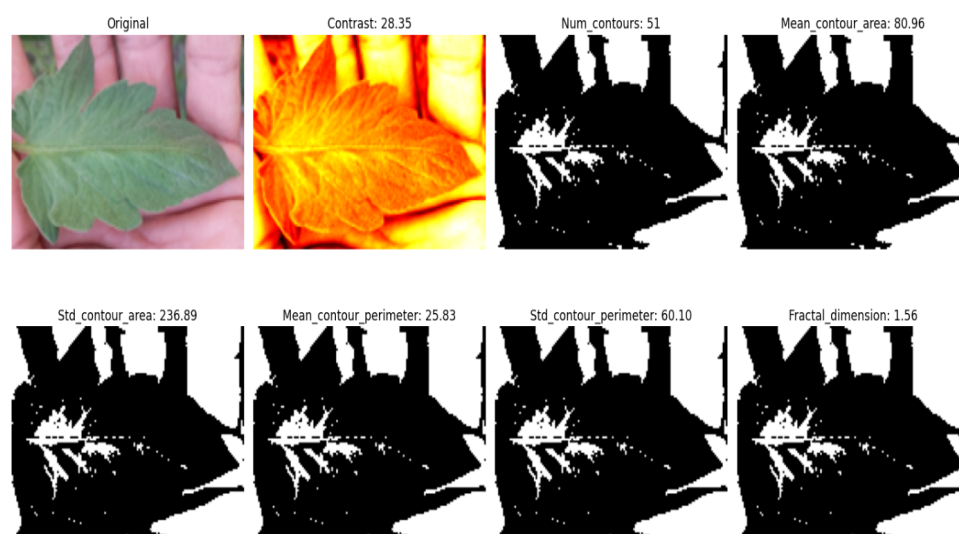


Figure 7. Examples of extracted texture, geometric, and fractal descriptors from tomato leaf images, including image contrast, contour-based characteristics, entropy measures, and fractal dimension used for multi-stage disease classification.

4.4. Assessment of Classification Effectiveness

To provide a reliable assessment of the proposed approach, the dataset containing 5245 images of tomato leaves was divided into training, validation, and test subsets using a 70:15:15 ratio. Images related to the same stage of the disease were assigned exclusively to one subset in order to reduce the risk of data leakage. All extracted features were normalized to the range $[0, 1]$ using Min–Max scaling before classifier training. Three machine learning algorithms, namely Random Forest (RF), XGBoost, and Support Vector Machine (SVM), were implemented and optimized using GridSearchCV with five-fold cross-validation. For the Random Forest classifier, the hyperparameter search included the number of trees (50, 100, and 200), maximum tree depth (None, 10, 20, and 30), minimum samples required for node splitting (2, 5, and 10), and minimum samples per leaf (1, 2, and 4). The optimal configuration consisted of 200 trees, a maximum depth of 20, a minimum split size of 2, and a minimum leaf size of 1. For XGBoost, the hyperparameter search considered the number of estimators (100, 200, and 400), maximum tree depth (3, 5, and 7), learning rate (0.05, 0.1, and 0.2), subsampling ratio (0.8 and 1.0), and column sampling ratio (0.8 and 1.0). The optimal parameters were 400 estimators, maximum depth of 5, learning rate of 0.2, subsample of 1.0, and colsample_bytree of 0.8. For the SVM classifier, a radial basis function (RBF) kernel was employed. The optimal hyperparameters obtained by grid search were $C = 1000$ and $\gamma = 0.1$. The models were evaluated on an independent test set using Accuracy, Precision, Recall, and F1-score metrics (Table 4).

Table 4. Comparison of the machine learning models for tomato late blight classification in five severity classes.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
RandomForest	88	88	86	86
XGBoost	92	92	90	91
Support Vector Machine (SVM)	93	92	92	92

A comparative analysis of the classification models shows that all the evaluated algorithms have achieved satisfactory performance in detecting the stages of late blight in tomatoes. Among the tested methods, SVM showed the highest accuracy (93.0%), followed by XGBoost (92.0%), while Random Forest achieved an accuracy of 88.0%. The obtained results show that the highlighted fractal and textural features provide sufficient discriminative ability for multi-stage classification of diseases. These results confirm the effectiveness of the proposed system of pretreatment and identification of signs for the diagnosis of plant diseases.

Rows in the confusion matrix (Figure 8) correspond to ground-truth labels, while columns represent predicted disease stages. The class labels correspond to: 0—healthy leaf, 1—initial stage (0.1–10% lesion area), 2—moderate stage (11–25% lesion area), 3—middle stage (26–50% lesion area), and 4—severe stage ($\geq 51\%$ lesion area). The Random Forest classifier (Figure 8a) demonstrates acceptable classification performance; however, several misclassifications occur between adjacent disease stages. The XGBoost model (Figure 8b) exhibits improved recognition capability, particularly for the intermediate stages of disease progression. Among all evaluated algorithms, the SVM classifier (Figure 8c) achieved the most balanced classification performance and the highest overall accuracy (93.0%), indicating a strong ability to distinguish visually similar disease stages. Most classification errors occurred between stages 1 and 2, as well as between stages 2 and 3. This can be explained by the similarity of lesion morphology during the intermediate stages of disease development. In contrast, severe disease stages were classified with higher accuracy because they are characterized by larger affected areas and more pronounced structural

changes. These results confirm that the extracted fractal and textural descriptors provide informative features for the multi-stage classification of tomato late blight.

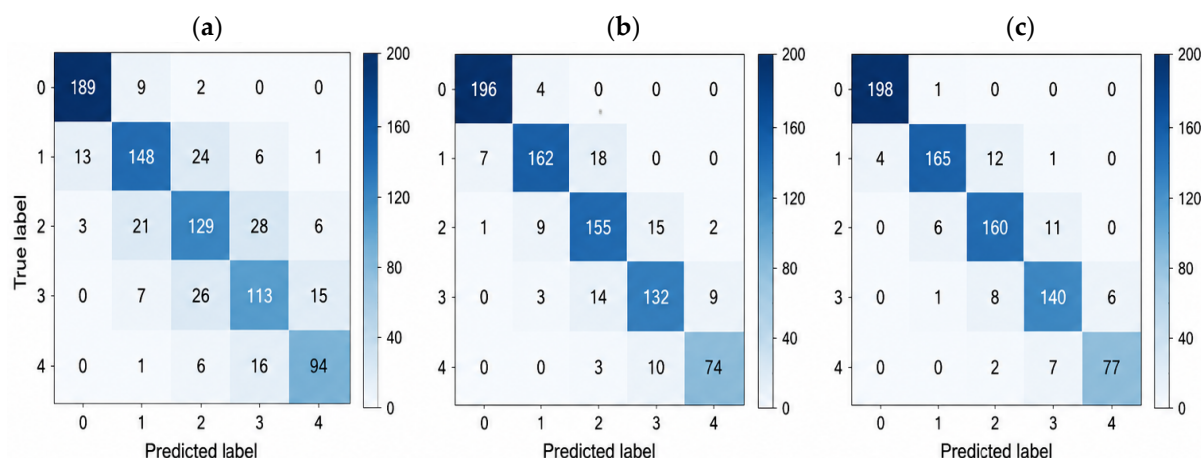


Figure 8. Confusion matrices of the Random Forest (RF), XGBoost, and Support Vector Machine (SVM) classifiers for multi-stage tomato late blight classification. All matrices were generated using the same independent test set ($n = 787$).

4.5. Ablation Study: The Effect of Fractal Features on Classification Efficiency

To assess the contribution of fractal descriptors to classification efficiency, an ablation study was conducted using various combinations of features. The results show that only textural features achieved accuracy of 84%, while only fractal features increased efficiency to 87%. The combination of textural and fractal descriptors provided the highest classification accuracy (93%), demonstrating the complementary nature of these features. The integration of fractal analysis improves the understanding of the structural complexity of the affected areas, thereby improving the recognition of various stages of tomato late blight (Table 5).

Table 5. Ablation study of different feature combinations using the SVM classifier.

Feature	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Texture only	84	83	82	82
Fractal only	87	86	85	85
Texture + Fractal	93	92	92	92

5. Discussion

The analysis of the generated data set confirms its suitability for use in machine learning systems in the diagnosis of late blight in tomatoes. The use of heterogeneous imaging devices and varying lighting conditions increases data variability and enhances the practical relevance of the dataset. The preprocessing pipeline, which includes grayscale conversion, median filtering, and the Otsu threshold, effectively reduced noise in the image and improved the extraction of informative areas related to disease progression.

The selected feature space combines textural, geometric, and fractal descriptors that allow quantitative characterization of affected leaf structures. The results show that an increase in the severity of the disease is associated with an increase in the structural complexity of the lesions, which is reflected in an increase in the values of the fractal dimension. This confirms that fractal analysis provides additional information beyond the usual texture features and improves understanding of the stages of disease progression.

Classification experiments have demonstrated the effectiveness of the proposed approach to feature extraction. Among the evaluated classifiers, SVM showed the highest

performance with 93.0% accuracy, followed by XGBoost (92.0%) and Random Forest (88.0%). The confusion matrices indicate a reliable separation of the stages of the disease, although minor classification errors persist for neighboring classes with similar visual characteristics.

The ablation study further confirmed the contribution of fractal descriptors. The combination of texture and fractal features made it possible to achieve better classification efficiency than individual groups of features, demonstrating that fractal characteristics provide additional information for determining the stage of the disease.

Despite these promising results, the dataset was collected under controlled greenhouse conditions, which may limit the generalization of data in open-ground conditions with a more diverse background and lighting conditions. Future work should focus on acquiring field-collected images, conducting cross-device validation experiments, and comparison with deep learning-based approaches to further evaluate the reliability and scalability of the proposed method.

Comparison with Deep Learning Approaches

To position the proposed approach within the context of recent advances in plant disease diagnosis, we compared our results with representative deep learning architectures reported in the literature. It should be noted that the methods listed in Table 6 are evaluated on different datasets with varying class compositions, image resolutions, and acquisition conditions. Therefore, the comparison is indicative rather than strictly equivalent, and should be interpreted as a general positioning of the proposed approach relative to the current state of the art. Recent studies have demonstrated that CNN-, ResNet50-, MobileNetV3-, EfficientNet-, and Vision Transformer-based models achieve high classification accuracy on plant disease datasets. However, most of these approaches operate directly on image pixels and require substantial computational resources and large-scale training data. In contrast, the proposed method relies on interpretable fractal and texture descriptors combined with conventional machine learning algorithms. This provides lower computational complexity while maintaining competitive classification performance and improved explainability for disease stage assessment.

Table 6. Comparison of the proposed Fractal + SVM approach with state-of-the-art deep learning architectures for tomato leaf disease classification, including an indicator of computational complexity.

Model	Dataset	Number of Classes	Parameters (in Millions)	Reported Accuracy (%)
CNN [26]	Tomato & Corn	4	3.2	97.5
ResNet50 [27]	Tomato Village	8	25.6	95.7
MobileNetV3 [28]	Tomato Disease	Multiple	5.4	94.9
Vision Transformer (ViT) [29]	Plant Disease	Multiple	86.0	96.0–98.0
Proposed Fractal + SVM	Proposed dataset	5	<0.1	93.0

Although the proposed Fractal + SVM approach achieves slightly lower classification accuracy than state-of-the-art deep learning architectures, it requires substantially lower computational resources and provides improved interpretability. Therefore, the proposed method represents an attractive trade-off between classification performance and computational complexity, particularly for resource-constrained agricultural applications.

6. Conclusions

In this study, a representative dataset of tomato leaf images reflecting five stages of late blight progression under greenhouse conditions was developed. The dataset contains 5245 images acquired using different imaging devices and varying acquisition conditions, increasing its diversity and practical relevance. The proposed preprocessing pipeline,

including grayscale conversion, median filtering, Otsu thresholding, and feature normalization, improved image quality and enabled reliable extraction of informative descriptors.

An important contribution of this work is the integration of fractal analysis with conventional texture and geometric features to characterize the structural complexity of diseased regions. The extracted feature space was used for classification experiments employing Random Forest, XGBoost, and Support Vector Machine classifiers. The obtained results demonstrated that SVM achieved the highest classification accuracy (93.0%), followed by XGBoost (92.0%) and Random Forest (88.0%), confirming the effectiveness of the proposed feature extraction approach for multi-stage disease identification.

Furthermore, the ablation study showed that combining texture and fractal features provides superior classification performance compared with individual feature groups, emphasizing the importance of fractal descriptors for representing disease progression patterns.

The developed dataset and proposed methodology can serve as a foundation for future research in plant disease diagnosis, agricultural monitoring, and precision farming applications. Future work should focus on expanding the dataset with field-acquired images, conducting additional cross-device validation experiments, and comparing the proposed approach with deep learning-based methods to further improve robustness and generalization capability.

In the future, it is planned to expand the dataset by including images obtained in the field, as well as increasing its volume and diversity. A promising direction is to conduct a comparative analysis of various feature extraction methods, including fuzzy descriptors [30] and multi-connected weights [31], and the development of hybrid models that improve the accuracy and stability of the classification of disease stages.

Author Contributions: Conceptualization, J.K. and I.S.; Methodology, B.A., S.O., T.K. and A.K.; Software, F.M. and M.H.; Validation, S.O., I.S. and A.K.; Formal analysis, F.M., M.H., B.A. and T.K.; Investigation, M.H. and T.K.; Resources, B.A., S.O. and T.K.; Data curation, J.K. and M.H.; Writing—original draft, F.M. and J.K.; Writing—review & editing, F.M., J.K. and A.K.; Visualization, B.A.; Supervision, S.O. and I.S.; Project administration, T.K., I.S. and A.K.; Funding acquisition, A.K. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Informed Consent Statement: Not applicable.

Data Availability Statement: The dataset is publicly available on the Github repository <https://github.com/BaxaDE/tomato-disease-dataset>, accessed on 2 February 2026.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Murugesan, S.; Chinnadurai, J.; Srinivasan, S.; Mathivanan, S.K.; Chandan, R.R.; Moorthy, U. Robust multiclass classification of crop leaf diseases using hybrid deep learning and Grad-CAM interpretability. *Sci. Rep.* **2025**, *15*, 29955. [CrossRef] [PubMed]
2. Xiang, Y.; Gao, S.; Li, X.; Li, S. DWTFormer: A frequency-spatial features fusion model for tomato leaf disease identification. *Plant Methods* **2025**, *21*, 33. [CrossRef]
3. *The United Nations Development Program and the UNF Green Climate Fund as Part of the Preparedness Program*; Sectoral Adaptation Plan of Agriculture of Uzbekistan for the Period 2025–2030 (Ru); Ministry of Ecology, Environmental Protection and Climate Change of the Republic of Uzbekistan: Tashkent, Uzbekistan, 2025.
4. Medina, D.P.; Crivello, A.; Sportelli, M.; Bianchini, M.; Cabrera, I.M. Web components for late blight (*Phytophthora infestans* (Mont.) De Bary) and early blight (*Alternaria solani* Sor.) outbreaks forecast on *Solanum tuberosum* L. in Cuba under future climate scenarios. *Smart Agric. Technol.* **2025**, *11*, 101003. [CrossRef]
5. Curado, R.; Gonçalves, P.; Marques, M.R.; Antunes, M. Pasture Plant's Dataset. *Data* **2026**, *11*, 63. [CrossRef]
6. Nasir, N.; Ramzan, S.; Basharat, A.; Jabbar, S.; Raza, A.; Kim, C.; Syafrudin, M.; Fitriyani, N.L. Interpretable deep multimodalbased tomato disease diagnosis and severity estimation. *Sci. Rep.* **2025**, *15*, 37919. [CrossRef]

7. Kumar, S.; Sharma, Y.K.; Kumar, M.; Lilhore, U.K.; Aldossary, S.M.A.; Simaiya, S.; Khan, M.M.; Hussien, S.A.; Ghith, E.S. A hybrid deep learning and fuzzy logic framework for robust tomato disease detection and classification. *Sci. Rep.* **2026**, *16*, 7002. [\[CrossRef\]](#)
8. Srinivasan, S.; Kumar, A.R.; Nagashree, B.A.; Tanwar, J.; Singh, V.P.; Moorthy, U. Multi-class classification of plant leaf diseases using a hybrid deep neural transformer system and explainable AI techniques. *Sci. Rep.* **2026**, *16*, 18161. [\[CrossRef\]](#) [\[PubMed\]](#)
9. Ouamane, A.; Chouchane, A.; Himeur, Y.; Debilou, A.; Amira, A.; Atalla, S.; Mansoor, W.; Al Ahmad, H. Enhancing Plant Disease Detection: A Novel CNN-Based Approach with Tensor Subspace Learning and HOWSVD-MD. *arXiv* **2024**, arXiv:2405.20058. [\[CrossRef\]](#)
10. Turatbekova, A.; Masharipova, M.; Umarova, F.; Khalmuradova, E.; Rustamova, R.; Abdixoshimov, M.; Teshaboyev, R. Research into biologically active plant terpenoids and the mechanisms underlying on biological activity. *E3S Web Conf.* **2024**, *563*, 03076. [\[CrossRef\]](#)
11. Zhang, X.; Xu, X. PlantClassiNet: A Dual-Modal Fine-Tuning Framework for CNN-Based Plant Disease Classification. *Appl. Sci.* **2025**, *16*, 170. [\[CrossRef\]](#)
12. Sherifi, S. A Compact and Efficient 1.251 Million Parameter Machine Learning CNN Model PD36-C for Plant Disease Detection: A Case Study. *arXiv* **2026**, arXiv:2604.11332. [\[CrossRef\]](#)
13. Ashurov, A.Y.; Al-Gaashani, M.S.A.M.; Samee, N.A.; Alkanhel, R.; Atteia, G.; Abdallah, H.A.; Saleh Ali Muthanna, M. Enhancing plant disease detection through deep learning: A Depthwise CNN with squeeze and excitation integration and residual skip connections. *Front. Plant Sci.* **2025**, *15*, 1505857. [\[CrossRef\]](#) [\[PubMed\]](#)
14. Sunday, B.; Yusuf, S.A.; Abdullahil, M.; Masha, Y.A.; Matemilola, A.S. Disorder severity classification in tomato based on weight cluster loss and convolutional neural network. *Discov. Appl. Sci.* **2025**, *7*, 1434. [\[CrossRef\]](#)
15. Oprisan, A.; Oprisan, S.A. Scaling of Haralick features with image bit depth and gray level co-occurrence matrix displacement vector for linear gradients. *Comput. Biol. Med.* **2025**, *196*, 110880. [\[CrossRef\]](#) [\[PubMed\]](#)
16. Nurmukhamedov, T.; Achilov, B.; Turdiev, O. Comparison of Fractal Compression Methods of Images. In *Proceedings of the 13th International Conference on Applied Applied Innovations in IT in IT (ICAIIIT)*; Hochschule Anhalt: Bernburg, Germany, 2025; Volume 13. [\[CrossRef\]](#) [\[PubMed\]](#)
17. Das, B.K.; Mohanta, D. Investigating textural fractals in Bougainvillea petals for wettability and biomimetic surface design. *Curr. Appl. Phys.* **2026**, *81*, 45–56. [\[CrossRef\]](#)
18. Tariq, M.H.; Sultan, H.; Akram, R.; Kim, S.G.; Kim, J.S.; Usman, M.; Gondal, H.A.H.; Seo, J.; Lee, Y.H.; Park, K.R. Estimation of Fractal Dimensions and Classification of Plant Disease with Complex Backgrounds. *Fractal Fract.* **2025**, *9*, 315. [\[CrossRef\]](#)
19. Kutlimuratov, A.; Achilov, B.; Seitnazarov, K.; Allayarov, P.; Saymanov, I.; Oteniyazov, R.; Khamzaev, J. XGBoost Ensemble Algorithm for Classifying Tomato Leaf Diseases Based on Texture Descriptors. *AgriEngineering* **2026**, *8*, 98. [\[CrossRef\]](#)
20. Czaja, M.; Skirlińska-Nosek, K.; Chachaj-Brekiesz, A.; Wnętrzak, A.; Lipiec, E. Combined non-negative matrix factorization and Otsu method for advanced analysis of Raman hyperspectral images acquired at nano- and microscale. *Opt. Commun.* **2025**, *591*, 132139. [\[CrossRef\]](#)
21. Jiang, Q.; Xiao, Y.; Zhou, G.; Liu, G.; Li, Z.; Luo, J.; He, K.; Liao, S. Integrating radius margin constraints and class variance for improved CNN-based image recognition. *Knowl.-Based Syst.* **2025**, *327*, 114188. [\[CrossRef\]](#)
22. Lin, X.; Zhang, D.; Li, Y.; Yang, Q.; Li, P.; Huang, W. Dynamic patch-level contrastive learning for image dehazing. *Pattern Recognit.* **2026**, *179*, 113529. [\[CrossRef\]](#)
23. Liu, Y.; Yin, J.; Chen, Y.; Wang, J.; Zhou, X.; Wang, X. PolyDiffusion: A Multi-Objective Optimized Contour-to-Image Diffusion Framework. *Comput. Mater. Contin.* **2025**, *85*, 3965–3980. [\[CrossRef\]](#)
24. Buchke, P.; Mayuri, A.V.R. A Hybrid Explainable Deep Learning and Spectral-Texture Ensemble Approach for Tomato Leaf Disease Diagnosis. *Eng. Technol. Syst.* **2026**, *36*, 97–113. [\[CrossRef\]](#)
25. Mehdizadeh, M.; Al-Taey, D.K.A.; Omid, A.; Abbood, A.H.Y.; Askar, S.; Topildiyev, S.; Pallathadka, H.; Asaad, R.R. Advancing agriculture with machine learning: A new frontier in weed management. *Front. Agric. Sci. Eng.* **2025**, *12*, 288–307. [\[CrossRef\]](#)
26. Yasin, A.; Fatima, R. On the Image-Based Detection of Tomato and Corn leaves Diseases: An in-depth comparative experiment. *arXiv* **2023**, arXiv:2312.08659. [\[CrossRef\]](#)
27. Sheenam; Sharma, K. Neural Network-Based Diagnostic Systems for Tomato Leaf Diseases in Smart Farming Environments. *Natl. Acad. Sci. Lett.* **2026**. Correction in *Natl. Acad. Sci. Lett.* **2026**. <https://doi.org/10.1007/s40009-026-02299-0>. [\[CrossRef\]](#)
28. Hoang, T.-M.; Bui, V.-H.; Nguyen, V.-S.; Doan, D.-T.; Dang, H.-A.; Pham, A.-T. A comprehensive evaluation of lightweight deep learning models for tomato disease classification on edge computing environments. *Sci. Rep.* **2026**, *16*, 12320. [\[CrossRef\]](#) [\[PubMed\]](#)
29. Gunasekaran, H.; Rajkumar, S.; Kirubadharsini, B.L. Lightweight deep learning for tomato disease detection: Trends, challenges, and edge AI perspectives. *Front. Plant Sci.* **2026**, *16*, 1737208. [\[CrossRef\]](#) [\[PubMed\]](#) [\[PubMed Central\]](#)

30. Madrakhimov, S.; Makharov, K.; Khurramov, A. On the Transparency of Decision-Making in Classification by Precedents with Fuzzy Descriptions. *IEEE Access* **2025**, *13*, 173656–173664. [[CrossRef](#)]
31. Rakhimovich, A.M.; Kadirbergenovich, K.K.; Ishkobilovich, Z.M.; Kadirbergenovich, K.J. Logistic Regression with Multi-Connected Weights. *J. Comput. Sci.* **2024**, *20*, 1051–1058. [[CrossRef](#)]

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.