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SPATIAL MULTI-SCALE FRACTAL ANALYSIS OF TOMATO LEAF STRUCTURAL DEGRADATION UNDER DISEASE PROGRESSION

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ABSTRACT

Tomato (*Solanum lycopersicum*) is an important horticultural crop worldwide, and its productivity is significantly limited by the widespread occurrence of foliar diseases that gradually modify leaf morphology and physiological function. Disease progression in the leaves entails intricate spatial transformations like lesion development, vein proliferation and disruption in venation, tissue necrosis and disruption of normal laminar architecture. Often, these structural alterations may be challenging to express in a conventional visual or categorical scoring system which is often subjective and lacks granularity. In the present study, a spatial multi-scale fractal analysis framework has been proposed for the quantitative capture of structural degeneration in tomato leaves during disease progression. Leaf images from sources with known disease severity levels were analyzed through fractal geometry-based metrics, focusing on two key descriptors.fractal dimension (FD) and lacunarity.to express structural complexity and heterogeneity. Fractal dimension serves as a description of overall morphological complexity in this context, whereas lacunarity is widely used to quantify spatial irregularity and gap distributions within leaf tissues. Multi-scale analysis was employed to examine structural changes at different spatial resolutions. This helped us better understand both global shape changes and localized tissue damage. The findings demonstrate a steady reduction in fractal dimension as disease severity escalates, indicating a gradual deterioration of structural complexity. On the other hand, lacunarity values increase as the disease gets worse, which means that the leaf architecture becomes more varied and broken up. The results show that fractal-based spatial analysis is a strong, non-destructive, and objective way to measure how disease damages the structure of plant leaves. This technique holds considerable promise for utilization in automated plant disease diagnostic systems, precision agriculture, and digital plant phenotyping platforms.

Keywords: Tomato (*Solanum lycopersicum*), plant pathology, fractal dimension, lacunarity, image analysis, leaf morphology, disease progression, multi-scale spatial analysis, structural degradation, digital phenotyping.

INTRODUCTION

Tomato (*Solanum lycopersicum*) is one of the most widely grown vegetables in the world. It is very important for global food security, nutrition, and the agricultural economy. But a lot of foliar diseases caused by fungi, bacteria, and viruses keep threatening tomato production. Diseases such as early blight, late blight, bacterial spot, and mosaic virus infection have a big impact on the structure of leaves, which makes them less able to photosynthesize, causes them to die too soon, and results in big losses in yield (Agrios, 2005).

The leaf is a very complicated biological structure that has a lot of different levels of organization, such as venation networks, epidermal patterns, and mesophyll arrangement. As the disease gets worse, this organized structure progressively deteriorates, which is shown by the formation of lesions, loss of chlorophyll, tissue necrosis, and damage to the vascular system. These structural changes aren't the same everywhere, and they often change depending on the size of the area being looked at. This makes it hard to measure them accurately using standard visual scoring methods (Barbedo, 2013).

Conventional methods for evaluating plant diseases rely primarily on subjective visual assessments or categorical indices of disease severity. Even though these methods are easy to use, they aren't very accurate, reliable, or sensitive to changes in structure that happen early on. Consequently, there is an increasing demand for sophisticated quantitative methodologies capable of precisely characterizing the progressive morphological changes occurring in infected plant tissues (Mohanty *et al*., 2016).

Benoit Mandelbrot came up with fractal geometry, which is a powerful way to use math to study natural structures that are complex and not perfectly regular. Biological systems, including leaves, roots, and vascular networks, frequently display self-similar and scale-invariant characteristics, rendering them appropriate for fractal-based analysis. Fractal dimension (FD) quantitatively assesses structural complexity, whereas lacunarity quantifies the heterogeneity and spatial distribution of gaps within a structure (Mandelbrot, 1982 and Cross, 1997).

In recent years, image-based fractal analysis has become a useful tool in plant phenotyping and pathology for finding small structural differences that people can't easily see (Backes *et al*., 2009). Nonetheless, the majority of studies concentrate on single-scale analysis, which may inadequately reflect the hierarchical characteristics of biological degradation processes.

To overcome this limitation, the present study applies a spatial multi-scale fractal analysis approach to investigate structural degradation in tomato leaves during disease progression. By integrating fractal dimension across multiple spatial scales, this study aims to provide a more comprehensive and quantitative understanding of how disease affects leaf architecture at both macro and micro structural levels.

The objective of this research is to establish a robust, non-destructive, and scalable framework for early detection and quantification of disease-induced morphological changes in tomato leaves, which can further contribute to the development of automated plant disease diagnostic systems.

MATERIALS AND METHODS

Dataset Source and Image Acquisition

The publicly available PlantVillage dataset has high-quality labeled images of healthy and diseased plant leaves taken under controlled conditions (Hughes and Salathé, 2015). We got tomato leaf images (Solanum lycopersicum) from this dataset.

For this study, images were categorized into three disease progression stages:

- Healthy (Control)
- Early infection stage
- Late infection stage

These categories represent progressive structural degradation in leaf morphology due to disease.

Image Preprocessing

Initial image preprocessing was performed using Fiji (ImageJ) to extract relevant structural features from the leaf images (Schindelin *et al*., 2012).

The preprocessing workflow included:

1. Conversion of RGB images into grayscale
2. Noise reduction using filtering techniques
3. Adjustment of brightness and contrast
4. Background removal to isolate the leaf region
5. Binary thresholding for segmentation of leaf structure

These steps ensured that only morphological features of the leaf were retained for subsequent analysis (Gonzalez and Woods, 2008).

Disease Progression Categorization

Leaf images were categorized into Healthy, Early, and Late infection stages based on visible symptoms such as lesion formation, discoloration, and tissue degradation (Barbedo, 2013). This classification enabled comparative analysis of structural changes associated with disease progression.

Multi-Scale Fractal Analysis

Fractal analysis was performed using a computational approach implemented in Python (Anaconda environment).

The box-counting method was used to compute fractal dimension (FD) from the binary leaf images (Mandelbrot, 1982). In this method, the image is overlaid with grids of varying box sizes, and the number of boxes containing part of the leaf structure is counted.

$$FD= \log N(\ ) / \log (1/\ )$$

Where: N( ) = number of occupied boxes, = box size

A multi-scale approach was applied by varying box sizes, allowing analysis of structural complexity at different spatial resolutions (Backes *et al*., 2009).

Spatial Heatmap Generation

Spatial heatmaps were generated using Python-based image processing techniques to visualize the distribution of structural intensity across the leaf surface.

Heatmaps enabled:

- Identification of regions with high structural degradation
- Visualization of lesion-dense areas
- Comparative assessment of spatial heterogeneity across disease stages

Graphical Representation

Graphical analysis was performed to illustrate variations in fractal dimension across disease stages.

Plots were generated using Python libraries (e.g., Matplotlib) to represent:

- Fractal dimension vs disease stage
- Comparative structural trends across categories
- These visualizations helped in clearly identifying trends in structural degradation.

Statistical Analysis

Statistical analysis was conducted using Microsoft Excel to evaluate the significance of differences in fractal dimension across disease stages.

The following statistical methods were applied:

- Calculation of mean and standard deviation for each group
- One-way Analysis of Variance (ANOVA) to test overall significance
- Post-hoc comparison using Tukey fs Honestly Significant Difference (HSD) test
- The Tukey HSD test was used to identify statistically significant differences between Healthy, Early, and Late stages of disease progression.ms and precision agriculture technologies.

RESULTS AND DISCUSSION

Fractal Dimension Analysis Across Disease Stages

Fractal dimension (FD) was used as a quantitative measure to evaluate the structural complexity of tomato leaves across different disease progression stages (Healthy, Early, and Late). The mean fractal dimension values obtained for each category are presented below:

Class	Mean FD
HEALTHY	1.923712
EARLY	1.67748
LATE	1.331023

Table 1. Multi scale fractal dimensions values

The results clearly indicate a progressive decline in fractal dimension with increasing disease severity. Healthy leaves exhibited the highest FD, reflecting a highly complex and well-organized structural architecture. In contrast, Early-stage leaves showed a moderate reduction, indicating initial disruption due to lesion formation. Late-stage leaves exhibited a substantial decrease in FD, suggesting severe structural degradation, fragmentation, and loss of venation integrity.

These findings are consistent with previous studies demonstrating that fractal dimension effectively captures structural complexity and its degradation in biological systems (Mandelbrot,1982 and Cross, 1997).

Figure 1. Mean fractal dimensions values across Healthy, Early, Late Stages

Multi-Scale Fractal Analysis

To better understand structural changes at different spatial resolutions, fractal dimension was analyzed at multiple scales (256, 128, and 64).

Scale	Healthy	Early	Late
256	1.923712	1.901043	1.901981
128	1.67748	1.610499	1.631949
64	1.331023	1.39625	1.471515

Table 2. Multi-scale fractal dimension values

At the macro-scale (256), minimal differences were observed among the three stages, indicating that overall leaf shape remains relatively unaffected during early disease progression.

At the meso-scale (128), a clear decline in FD from Healthy to Early stage was observed, suggesting initial structural disruption at intermediate levels such as lesion formation and tissue disorganization.

At the micro-scale (64), Late-stage leaves showed a higher FD compared to Healthy and Early stages, indicating increased structural irregularity and fragmentation at finer spatial levels.

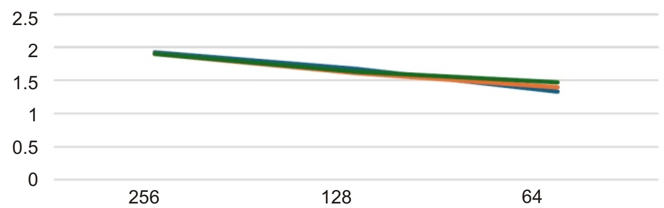

Figure 2. Variation of fractal dimensions across multiple spatial scales (256,128,64) for different disease stages.

These observations confirm that disease progression is scale-dependent, with more pronounced effects observed at smaller spatial scales (Backes *et al*., 2009).

Statistical Analysis (ANOVA) scale

To determine whether the differences in fractal dimension across disease stages were statistically significant, a one-way ANOVA was performed.

- F-value: 564.7652665834562
- p-value: $7.76697746435071 \times 10.6^{1}$

The extremely high F-value indicates substantial variation among the groups, while the very low p-value ($p \ll 0.05$) confirms that the differences are highly statistically significant. This demonstrates that disease progression has a strong and measurable impact on leaf structural complexity (Montgomery, 2017).

Post-hoc Analysis (Tukey HSD Test)

To further examine pairwise differences between disease stages, Tukey's Honestly Significant Difference (HSD) test was performed (Tukey, 1949).

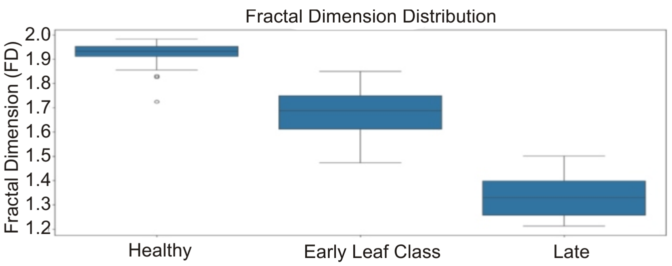

Figure 3. Post-hoc Tukey HSD test showing pairwise comparison of fractal dimension between Healthy, Early, and Late stages

Spatial Heatmap Analysis

Spatial heatmaps were used to visualize the distribution of structural complexity across leaf surfaces.

Healthy samples exhibited dense and continuous high-intensity regions, indicating uniform and intact structural organization.

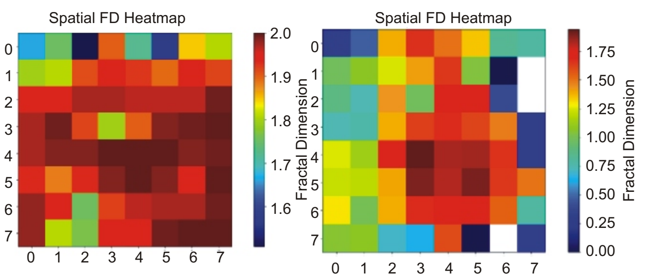

Figure 4. Spatial Heatmaps Showing Distribution Of Structural Complexity In Tomato Leaves 1 And 2 in Healthy

Early-stage samples showed mixed intensity patterns, reflecting localized disruption and partial structural degradation.

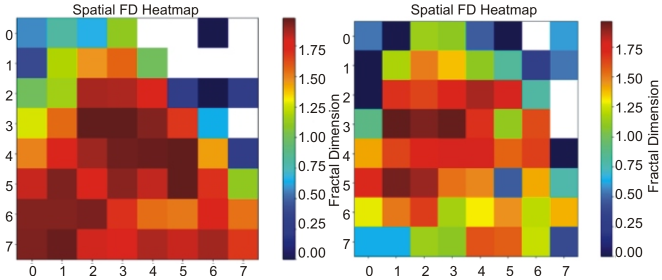

Figure 5. Spatial Heatmaps Showing Distribution Of Structural Complexity In Tomato Leaves 1 And 2 in Early.

Late-stage samples displayed highly heterogeneous and fragmented intensity distributions, indicating severe structural breakdown and loss of connectivity.

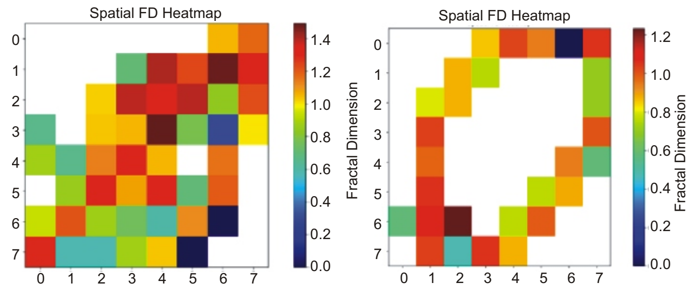

Figure 6. Spatial Heatmaps Showing Distribution Of Structural Complexity In Tomato Leaves 1 And 2 in Late

These spatial patterns clearly demonstrate that structural degradation becomes more localized and irregular as disease progresses, consistent with image-based plant disease analysis approaches (Barbedo, 2013).

Integrated Discussion

The results of this study clearly demonstrate that fractal dimension is a robust and sensitive parameter for quantifying structural degradation in tomato leaves during disease progression.

The observed decline in FD from Healthy to Late stages reflects a systematic loss of morphological complexity associated with tissue damage, lesion expansion, and venation disruption.

Multi-scale analysis further reveals that disease impact is not uniform across spatial levels. While macro-scale structures remain relatively stable during early stages, significant alterations occur at meso- and micro-scales, particularly in advanced infection stages. The increase in FD at micro-scale in Late-stage leaves suggests increased fragmentation and irregularity, which is characteristic of severe tissue breakdown.

The statistical analysis strongly supports these findings, confirming that the observed differences are highly significant and not due to random variation. The boxplot distribution further highlights the increasing variability and heterogeneity associated with disease progression.

Heatmap analysis provides complementary visual evidence, illustrating the transition from uniform structural organization in Healthy leaves to highly fragmented and irregular patterns in Late-stage leaves. This confirms that disease progression is both quantitatively measurable and spatially characterized.

Overall, the integration of fractal analysis, multi-scale evaluation, statistical validation, and spatial visualization provides a comprehensive framework for understanding disease-induced structural degradation. This approach offers a significant improvement over traditional qualitative methods and has strong potential for application in automated plant disease detection and precision agriculture systems.

CONCLUSION

The present study demonstrates that spatial multi-scale fractal analysis is an effective and reliable approach for quantifying structural degradation in tomato (*Solanum lycopersicum*) leaves under disease progression. The results clearly indicate a progressive decline in fractal dimension from Healthy to Late infection stages, reflecting a systematic loss of structural complexity associated with tissue damage, lesion expansion, and disruption of venation networks.

Multi-scale analysis revealed that the impact of disease is not uniform across spatial levels. While minimal variation was observed at the macro-scale, significant structural changes were evident at meso- and micro-scales, particularly in advanced stages of infection. This highlights the importance of scale-dependent analysis in capturing subtle morphological variations (Backes *et al*., 2009).

Spatial heatmap analysis further supported these findings by demonstrating a transition from uniform and continuous structural patterns in Healthy leaves to highly heterogeneous and fragmented distributions in Late-stage infected leaves. This confirms that disease progression leads to localized structural disruption and increased irregularity, consistent with image-based plant disease assessment approaches (Barbedo, 2013).

Statistical validation using ANOVA and Tukey HSD test confirmed that the differences in fractal dimension across disease stages are highly significant, establishing fractal dimension as a robust quantitative indicator of disease severity (Montgomery, 2017).

Overall, the integration of fractal analysis, multi-scale evaluation, spatial visualization, and statistical validation provides a comprehensive and objective framework for plant disease assessment. This approach has strong potential for application in digital plant pathology, automated disease detection systems, and precision agriculture for real-time crop health monitoring.

FUTURE SCOPE

The present study highlights the potential of spatial multi-scale fractal analysis as a quantitative tool for assessing structural degradation in plant leaves. Future research can integrate this approach with machine learning and deep learning techniques to enable automated and real-time disease detection systems.

Further expansion of this methodology to different crop species and disease types would improve its applicability in agricultural diagnostics. Additionally, combining fractal parameters with other image-based features, such as color and texture, may enhance the accuracy of disease severity estimation.

The use of advanced imaging technologies, including hyperspectral imaging and drone-based platforms, may facilitate large-scale field monitoring. Such developments can contribute significantly to precision agriculture by enabling early disease detection and improving crop management strategies.

CONFLICT OF INTREST

The authors declare that there is no conflict of interest.

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