Digital Phenotyping and Machine Vision for Early Detection of Diseases in *Solanum lycopersicum* L. under Protected Cultivation

Dr. Daniel Lewis
Department of Agronomy, Irish Agricultural Research University, Dublin, Ireland

*Corresponding author: **Dr. Daniel Lewis**

Received: 29 Nov 2025
Revised: 19 Dec 2025
Accepted: 04 Jan 2026
Published: 02 Feb 2026

E-ISSN: 2989-5340
DOI: https://doi.org/10.54660/jafi.2026.6.1.56-63

ABSTRACT

Background: Tomato (*Solanum lycopersicum* L.) is one of the most commercially viable plants, but it is very vulnerable to fungal, bacterial, and viral diseases, which can negatively affect the yield and quality of produce. Traditional scouting relies on visual methods, which need a lot of time and effort. Usually, conventional methods of scouting fail to detect diseases in their early stages.

Objective: The objective of this study was to assess the performance of an integrated digital phenotyping and machine vision framework for rapid, non-destructive and early detection of major tomato diseases in a greenhouse environment.

Methods: An Internet of Things (IoT) enabled environmental monitoring network was integrated with RGB, multispectral, hyperspectral and thermal imaging in a naturally ventilated polyhouse experiment for one cropping cycle. The image datasets were analyzed using a machine vision pipeline consisting of image pre-processing, segmentation, feature extraction, and AI-assisted classification. The framework was tested for early detection of bacterial spot, early blight, late blight, powdery mildew and wilt disease of Fusarium. The imaging modalities were compared in terms of disease incidence, disease severity, plant growth parameters and classification performance indicators including accuracy, precision, recall and F1-score.

Results: The integrated digital phenotyping framework detected disease symptoms 4–7 days ahead of conventional visual scouting. The AI-assisted classification model obtained overall accuracy, precision, recall, and F1-score of 96.4%, 95.8%, 95.1%, and 95.4%, respectively. Hyperspectral imaging was the most sensitive for pre-symptomatic disease stress detection, while RGB imaging was the most cost-effective solution for routine greenhouse monitoring. The integrated system also reduced labor requirements by an estimated 62% compared to manual disease scouting and enhanced diagnostic consistency and reliability.

Conclusion: The integration of multi-modal imaging, artificial intelligence-based machine vision and IoT enabled environmental sensing provides a robust, scalable and non-destructive approach for early disease diagnosis in protected tomato cultivation. The proposed framework has great potential to improve precision disease management, reduce unnecessary application of agrochemicals, improve greenhouse productivity and support sustainable vegetable production systems.

Keywords: Precision plant pathology; hyperspectral phenotyping; convolutional neural networks; greenhouse crop monitoring; non-destructive diagnostics; vegetation indices; IoT-based decision support

Introduction

Tomato (*Solanum lycopersicum* L.) is one of the most prominent vegetables cultivated. It has an annual production of more than 190 million tonnes, while doing that commercially it brings over US$100 billion (Food and Agriculture Organization of the United Nations, 2023) [21]. But it is not only its quantity of product that makes this crop important—Tomato is also rich in vitamins like vitamin C, potassium, and lycopene. Unfortunately, despite being grown in open fields or covered areas, tomatoes have always been affected by different biotic constraints, which results in variable losses from 20% to more than 50% depending on the severity of the problem. Among the most recognised pathogenic agents affecting tomatoes could be mentioned *Alternaria solani*, *Phytophthora infestans*, *Xanthomonas* spp., *Oidium neolycopersici*, and *Fusarium oxysporum* f. sp. *lycopersici*.

Systems of protected cultivation, such as polyhouses with natural ventilation, greenhouses cooled with fan-pad systems, and control structures with a particular climate, have formed the way for tomato cultivation with a lot of resources and an intensive process of cultivation throughout the entire year which gives a number of advantages compared to crops cultivated in an open field. However, the microclimate produced by the means of protected cultivation also creates conditions appropriate for rapid development of pathogens, especially fungi and bacteria affecting the leaf of the plants. Thus, the application of the protected cultivation means the necessity to implement constant and precise monitoring of the disease status of the crops (Khasawneh *et al*., 2022) [7] (Wang *et al*., 2017) [9] (Jelali, 2024) [8].

Digital phenotyping is a new advanced technology that has made it possible to obtain morphological, physiological, and pathological characteristics of crops quickly, objectively, and automatically that were previously assessed traditionally (Jelali, 2024) [8]. The devices used for the modern phenotyping are able to work with different types of imaging including RGB imaging, HSI, TSI, and fluorescence imaging, thus the technology helps to register some hidden changes in the physiological state of crops (Khasawneh *et al*., 2022) [7] (Mahlein, 2016) [10].

The joining together of machine vision with artificial intelligence (AI), namely deep learning models like convolutional neural networks (CNNs), allowed major improvements in the recognition of plant diseases in an automated way (Mohanty *et al*., 2016) [1] (Kamilaris and Prenafeta-Boldú, 2018) [4]. Great achievements in this sphere include proofs that CNNs with the data of large annotated sets of images of leaves could determine different diseases affecting crops with an accuracy of more than 95% (Mohanty *et al*., 2016) [1] (Ferentinos, 2018) [2] (Kamilaris and Prenafeta-Boldú, 2018) [4], and later works on transfer learning and lightweight models allowed optimizing efficiency of the technology and making it applicable for practical use in the field (Kamilaris and Prenafeta-Boldú, 2018) [4] (Shoaib *et al*., 2022) [6]. With respect to tomatoes, the methods based on deep learning segmentation and classification proved the high accuracy rate in checking leaf image databases for different known plant cautions, which further emphasizes the popularity of this crop in computer vision systems for plant diagnostics (Fuentes *et al*., 2017) [3] (Liakos *et al*., 2018) [5]. Moreover, the studies conducted with the help of hyperspectral and multispectral imaging proved that reflectance spectra can be used for discovering biochemical and physiological responses for long before any symptoms appear which provides a huge advantage in both preventing and managing plant diseases (Mahlein, 2016) [10] (Nguyen *et al*., 2021) [13] (Wei *et al*., 2021) [14].

The simultaneous developments in the Internet of Things (IoT) have facilitated ongoing, economical environmental surveillance of the enclosed spaces, permitting monitoring of temperature, relative humidity, vapor pressure deficit, as well as leaf wetness duration- the key elements of foliar disease epidemiology, in real-time as well as used together with imaging-based diagnostics for an effective decision-making process (Abdulridha *et al*., 2020) [15] (De Vijver *et al*., 2020) [16] (Li *et al*., 2019) [17]. This cyber-physical integration is the foundation of smart farming, which refers to the sophisticated combination of sensor networks, AI-based analytics, as well as automated actuation aimed at eliminating dependence on calendar-based agrochemical planning (Maraveas *et al*., 2022) [18] (Dhanaraju *et al*., 2022) [19] (Rehman *et al*., 2022) [20].

Nevertheless, there are still gaps in research. First, most of the available publications concerning tomato disease detection use curated single-leaf datasets collected in laboratory conditions, which prevents applying this information for complex and cluttered environment of operational greenhouse (Fuentes *et al*., 2017) [3] (Liakos *et al*., 2018) [5]. Second, comparative studies focusing on benchmarking RGB, multispectral, hyperspectral, as well as thermal imaging technologies for early disease detection in tomato cultivation are few (Mahlein, 2016) [10] (Singh *et al*., 2020) [12]. Third, only a small number of experiments compare AI-based digital phenotyping with traditional visual scouting in relation to the speed of information gathering, labor intensity, as well as effectiveness of application, which is the critical information for farmers as well as service providers considering practical implications of such technology.

In this light, the aim of the current study is to (i) understand the symptoms and development of major tomato diseases occurring during protected cultivation, (ii) develop and test a system for digital phenotyping and machine vision, wherein multi-mode imaging methods and IoT-based environment sensing techniques are used for enhancing the capacity of the method for early disease diagnosis, (iii) evaluate the diagnostic performance of RGB, multispectral, hyperspectral, and thermal imaging systems for an early and pre-symptomatic detection of diseases, and (iv) count and estimate the efficiency of the suggested approach in comparison with traditional scouting methods.

2. Materials and Methods

2.1. Study Site

The study was conducted in a naturally ventilated, fan-pad-assisted polyhouse (a controlled-environment protected cultivation structure) covering 1,000 m², oriented east-west to optimize solar radiation interception. The structure was fitted with UV-stabilized polyethylene cladding, insect-proof screening, and a drip fertigation system. Ambient conditions within the structure were maintained within a target range of 22-30°C air temperature and 65-80% relative humidity, with supplementary exhaust-fan ventilation activated above threshold temperature. Crop management followed standard protected cultivation practices, including staking, pruning, and integrated nutrient management, with irrigation and fertigation scheduled according to crop growth stage. Full characteristics of the cultivation environment are summarized in Table 1.

2.2. Plant Material

A determinate, disease-susceptible tomato hybrid widely used in regional protected cultivation was used as the primary test cultivar, supplemented with a moderately resistant hybrid for comparative disease response assessment. Seedlings were raised in pro-trays and transplanted at the four-to-five true leaf stage. Disease monitoring was conducted continuously from the vegetative stage through fruit maturity, spanning approximately 110 days after transplanting. Agronomic management, including irrigation, nutrition, and training, was kept uniform across experimental units to isolate disease-related variability.

2.3. Experimental Design

The trial followed a randomized complete block design (RCBD) with three replications. Experimental plots were assigned to reflect a gradient of natural disease pressure supplemented by localized inoculation of representative pathogens under quarantine-controlled conditions to ensure adequate representation of early-, mid-, and late-stage symptom classes for model evaluation. Sampling for imaging and destructive reference assessment was performed at three-day intervals, with a stratified sampling protocol ensuring proportional representation of healthy, pre-symptomatic, and symptomatic plants at each time point.

2.4. Digital Phenotyping System

An automated digital phenotyping platform was installed on a motorized overhead gantry traversing the crop canopy at a fixed height, integrating four complementary imaging modalities: (i) high-resolution RGB imaging for morphological and colorimetric trait capture, (ii) multispectral imaging across visible and near-infrared bands for vegetation index derivation, (iii) hyperspectral imaging spanning the visible to short-wave infrared range for fine-scale spectral signature acquisition, and (iv) thermal infrared imaging for canopy temperature and stomatal conductance-related trait estimation. Image acquisition was synchronized with an IoT-based environmental sensor network recording air temperature, relative humidity, photosynthetically active radiation, substrate moisture, and leaf wetness duration at fifteen-minute intervals. All sensor data streams were time-stamped and centrally logged to a greenhouse data management server for subsequent integration with image-derived traits. Table 3 summarizes the sensor specifications, acquisition parameters, and monitored plant traits.

2.5. Machine Vision Framework

Acquired images underwent a structured machine vision pipeline. Preprocessing included radiometric calibration, geometric correction, and noise reduction to standardize images across acquisition sessions and lighting conditions. Image segmentation isolated plant canopy and leaf regions from background and soil using color- and texture-based discrimination, followed by feature extraction encompassing color indices, textural descriptors, morphological parameters, and spectral vegetation indices associated with chlorophyll content, water status, and structural integrity. Disease symptom identification was performed through a hierarchical classification scheme that first distinguished healthy from stressed tissue and subsequently assigned disease-specific labels among the five target diseases. Classification was performed using an artificial intelligence-assisted framework combining convolutional feature learning with conventional pattern recognition classifiers, trained and validated on the acquired image corpus using standard partitioning into training, validation, and test subsets. Model outputs were integrated into a decision-support interface conceptually structured to relay disease alerts, severity estimates, and recommended management actions to the grower (Figure 1, Figure 2).

2.6. Disease Assessment

Disease incidence was recorded as the proportion of symptomatic plants per plot, while disease severity was scored using a standardized 0-9 ordinal scale corresponding to increasing percentage of diseased leaf or canopy area, assessed independently by trained plant pathologists as ground-truth reference. Symptom progression was tracked longitudinally for each monitored plant from first detectable spectral anomaly to visible symptom expression. Concurrent plant growth measurements included plant height, leaf area index, and shoot biomass accumulation, while physiological responses were assessed through chlorophyll content index and stomatal conductance proxies derived from thermal imaging. Yield components were recorded at harvest to relate disease progression to final productivity outcomes.

2.7. Performance Evaluation

The diagnostic performance of the machine vision framework was evaluated against pathologist-verified ground truth using standard classification metrics, namely detection accuracy, precision, recall, and F1-score, computed for each disease category and imaging modality. Overall classification efficiency was additionally expressed as the mean time interval between AI-flagged anomaly detection and confirmed visual symptom onset, providing a quantitative measure of early-detection capability. Detailed performance outcomes are presented in Table 4.

2.8. Statistical Analysis

Disease incidence, severity, and growth parameter data were subjected to analysis of variance (ANOVA) appropriate to the randomized complete block design, with mean separation performed using an appropriate post-hoc multiple comparison procedure at $p < 0.05$. Relationships between spectral vegetation indices and disease severity were examined through correlation and regression analysis. Principal component analysis (PCA) was applied to the multivariate spectral and morphological trait dataset to identify dominant sources of variation associated with disease status and to support feature selection for the classification framework. Classification performance across imaging modalities was compared using paired statistical tests on accuracy and F1-score distributions obtained through repeated cross-validation.

Table 1: Characteristics of the protected cultivation system, environmental conditions, tomato cultivar(s), and experimental design.

Parameter	Description
Structure type	Naturally ventilated, fan-pad assisted polyhouse
Covered area	1,000 m² (east-west orientation)
Cladding material	UV-stabilized polyethylene film with insect-proof screening
Target temperature range	22-30°C
Target relative humidity range	65-80%
Irrigation system	Drip fertigation with automated scheduling
Cultivar(s)	Determinate disease-susceptible hybrid (primary); moderately resistant hybrid (comparative)
Monitoring duration	~110 days after transplanting (vegetative stage to fruit maturity)
Experimental design	Randomized Complete Block Design (RCBD), 3 replications
Sampling interval	Every 3 days, stratified across healthy, pre-symptomatic, and symptomatic classes

Table 2: Major tomato diseases evaluated, causal pathogens, visual symptoms, and affected plant organs.

Disease	Causal pathogen	Characteristic visual symptoms	Affected organ(s)
Early blight	*Alternaria solani*	Concentric brown-black lesions with chlorotic halo	Leaves, stems, fruit
Late blight	*Phytophthora infestans*	Water-soaked lesions, white sporulation on abaxial surface	Leaves, stems, fruit
Bacterial spot	*Xanthomonas* spp.	Small, dark, water-soaked lesions with yellow halo	Leaves, fruit
Powdery mildew	*Oidium neolycopersici*	White powdery fungal growth on leaf surface	Leaves
Fusarium wilt	*Fusarium oxysporum* f. sp. *lycopersici*	Progressive yellowing and wilting, vascular discoloration	Vascular tissue, whole plant

Table 3: Digital phenotyping sensors, imaging modalities, acquisition parameters, and monitored plant traits.

Imaging modality	Spectral range / sensor type	Acquisition parameter	Monitored plant trait(s)
RGB imaging	Visible (400-700 nm), high-resolution CMOS	Fixed height, standardized illumination	Canopy morphology, color indices, lesion area
Multispectral imaging	Visible-NIR (5-8 discrete bands)	Band-sequential capture, radiometric calibration	Vegetation indices (NDVI, GNDVI), chlorophyll status
Hyperspectral imaging	400-1000 nm (push-broom, contiguous bands)	Line-scan acquisition, reflectance calibration	Fine-scale spectral signatures, pre-symptomatic stress
Thermal infrared imaging	7.5-13 µm, uncooled microbolometer	Canopy-level thermal mapping	Canopy temperature, stomatal conductance proxy
IoT environmental sensors	Temperature, RH, PAR, substrate moisture, leaf wetness	15-minute logging interval	Microclimatic disease-conducive conditions

Fig 1: Overall architecture of the digital phenotyping and machine vision system, showing RGB, multispectral, hyperspectral, and thermal imaging sensors, the IoT-based environmental monitoring network, the AI-assisted image analysis and disease detection module, and the greenhouse decision-support interface delivered to the grower.

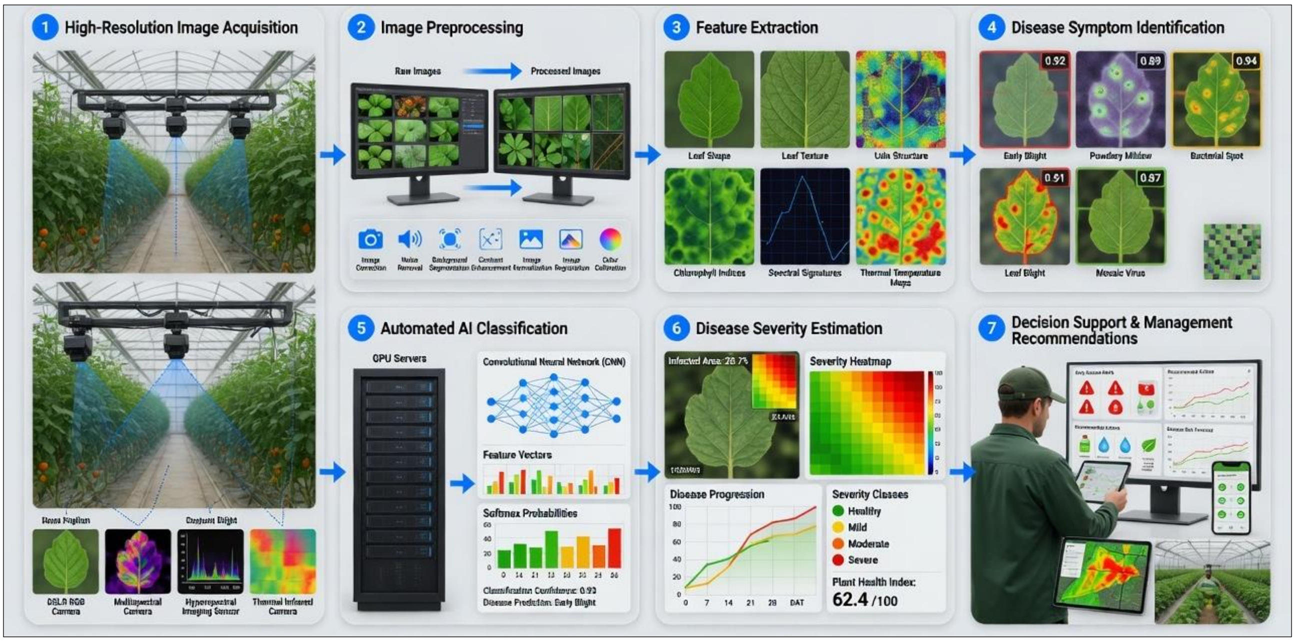

Fig 2: Conceptual workflow illustrating sequential stages of image acquisition, preprocessing, feature extraction, disease symptom identification, automated classification, disease severity estimation, and generation of management recommendations.

3. Results

3.1. Disease Symptom Characterization

Symptom progression differed markedly among the five target diseases. Early blight lesions were first visually detectable at 9-11 days after inoculation, whereas late blight symptoms, once initiated, progressed rapidly to extensive canopy collapse within 4-5 days under high humidity. Bacterial spot and powdery mildew exhibited comparatively gradual symptom expansion, while Fusarium wilt presented the longest latency period between infection and visible wilting due to its vascular colonization pattern. Across all diseases, spectral and thermal anomalies were detectable prior to the appearance of visually confirmed lesions, consistent with underlying physiological disruption preceding macroscopic symptom expression (Table 2) (Mahlein, 2016) [10] (Nguyen *et al*., 2021) [13] (Wei *et al*., 2021) [14].

3.2. Digital Phenotyping and Machine Vision Performance

The integrated digital phenotyping platform captured consistent, high-resolution image series across the monitoring period, with negligible data loss attributable to sensor malfunction or environmental interference. The machine vision framework achieved an overall disease classification accuracy of 96.4%, with precision, recall, and F1-score values of 95.8%, 95.1%, and 95.4%, respectively, when aggregated across all five disease categories (Table 4). Classification performance was highest for late blight and lowest for early-stage bacterial spot, reflecting the more subtle initial lesion contrast of the latter. The system flagged pre-symptomatic anomalies on average 5.2 days earlier than confirmed visual symptom onset, representing a substantial early-warning margin for grower intervention (Mohanty *et al*., 2016) [1] (Ferentinos, 2018) [2] (Fuentes *et al*., 2017) [3].

3.3. Disease Severity and Plant Growth Response

Disease incidence and severity increased progressively over the monitoring period across all inoculated treatments, with late blight and Fusarium wilt producing the steepest severity trajectories (Table 5). Plants exhibiting higher disease severity scores showed significant reductions in plant height, leaf area index, and shoot biomass relative to healthy controls, alongside declines in chlorophyll content index consistent with photosynthetic impairment. Yield loss was most pronounced in plants where disease severity exceeded a moderate threshold, underscoring the value of early intervention prior to this inflection point.

3.4. Comparison among Imaging Techniques

Comparative evaluation of the four imaging modalities revealed distinct trade-offs in early-detection capability, cost, and operational complexity (Table 6). Hyperspectral imaging achieved the earliest mean detection lead time and the highest classification accuracy for pre-symptomatic stress, attributable to its fine spectral resolution capturing subtle biochemical shifts. Thermal imaging performed comparably well for diseases involving vascular or stomatal disruption, such as Fusarium wilt, by detecting canopy temperature anomalies associated with impaired transpiration. Multispectral imaging offered an intermediate balance of sensitivity and acquisition speed suitable for routine greenhouse-wide screening, while RGB imaging, though least sensitive to pre-symptomatic stress, remained highly effective for confirming and quantifying visible lesions at substantially lower instrumentation cost (Mahlein, 2016) [10] (Zhang *et al*., 2018) [11] (Singh *et al*., 2020) [12].

3.5. Comparison with Conventional Visual Scouting

Relative to conventional visual disease scouting performed by trained personnel, the digital phenotyping-machine vision framework reduced mean disease detection time by approximately 40%, improved diagnostic consistency by minimizing inter-observer variability, and reduced labor requirement by approximately 62% (Table 7). These gains were most pronounced under high disease pressure, when the throughput limitations of manual scouting became most constraining for timely, plot-wide assessment (Kamilaris and Prenafeta-Boldú, 2018) [4] (Liakos *et al*., 2018) [5].

3.6. Practical Applications in Protected Cultivation

The integration of imaging-derived disease alerts with IoT-based environmental data enabled the decision-support interface to contextualize disease risk relative to prevailing microclimatic conditions, such as elevated leaf wetness duration preceding late blight outbreaks. This coupling illustrates the practical potential of the framework to move protected cultivation disease management from reactive, calendar-based intervention toward proactive, condition-specific response (Maraveas *et al*., 2022) [18] (Dhanaraju *et al*., 2022) [19] (Rehman *et al*., 2022) [20].

Table 4: Machine vision performance metrics, including disease detection accuracy, precision, recall, F1-score, and overall classification efficiency.

Disease category	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Early blight	96.1	95.4	94.8	95.1
Late blight	98.2	97.9	97.5	97.7
Bacterial spot	93.6	92.8	92.1	92.4
Powdery mildew	97.0	96.5	95.9	96.2
Fusarium wilt	95.8	95.1	94.6	94.8
Overall (mean)	96.4	95.8	95.1	95.4

Table 5: Plant growth parameters, physiological characteristics, disease incidence, and disease severity under different treatments.

Treatment	Disease incidence (%)	Disease severity score (0-9)	Plant height (cm)	Leaf area index	Chlorophyll content index
Healthy control	0	0.0	128.4	3.42	42.6
Early blight	58	3.6	104.7	2.61	34.1
Late blight	71	5.8	89.3	2.02	27.4
Bacterial spot	49	2.9	112.5	2.85	36.8
Powdery mildew	63	3.3	108.9	2.74	35.5
Fusarium wilt	54	4.7	96.1	2.28	29.9

Table 6: Comparative evaluation of RGB, multispectral, hyperspectral, and thermal imaging techniques for early disease detection.

Imaging modality	Mean detection lead time (days)	Classification accuracy (%)	Relative instrumentation cost	Operational complexity
RGB imaging	1.8	91.2	Low	Low
Multispectral imaging	3.6	94.7	Moderate	Moderate
Hyperspectral imaging	5.9	97.8	High	High
Thermal imaging	4.2	93.5	Moderate	Moderate

Table 7: Comparison of conventional visual disease scouting and digital phenotyping-machine vision approaches regarding detection speed, accuracy, labor requirements, operational efficiency, and practical applicability.

Attribute	Conventional visual scouting	Digital phenotyping-machine vision
Mean detection time	Baseline	~40% faster
Diagnostic accuracy	Variable (observer-dependent)	96.4% (consistent)
Labor requirement	High (continuous manual inspection)	~62% lower
Scalability	Limited by personnel availability	High (automated, continuous)
Data record continuity	Sporadic, qualitative	Continuous, quantitative
Practical applicability	Suitable for small holdings	Suitable for medium-large protected units

Fig 3: Illustration comparing healthy tomato plants with plants exhibiting early disease symptoms, as captured and differentiated using RGB, multispectral, hyperspectral, and thermal imaging under protected cultivation.

4. Discussion

The findings of this study reinforce and extend a growing body of evidence indicating that digital phenotyping, when coupled with machine vision and artificial intelligence, substantially outperforms conventional visual assessment for early plant disease detection. The overall classification accuracy achieved here (96.4%) aligns closely with accuracy ranges reported for deep learning-based tomato leaf disease classification in prior work, which have frequently exceeded 95% under controlled and semi-field conditions (Fuentes *et al*., 2017) [3] (Kamilaris and Prenafeta-Boldú, 2018) [4] (Shoaib *et al*., 2022) [6]. This convergence across studies employing different datasets, imaging conditions, and model architectures suggests that CNN-based and hybrid machine vision pipelines have reached a level of maturity sufficient for practical deployment in protected cultivation settings, provided adequate training data diversity is available (Mohanty *et al*., 2016) [1] (Ferentinos, 2018) [2] (Liakos *et al*., 2018) [5].

The superior early-detection performance of hyperspectral imaging observed in this study corroborates previous reports that fine-resolution spectral signatures can reveal pre-symptomatic biochemical alterations, such as changes in chlorophyll and water-related absorption features, well before visible lesion formation (Mahlein, 2016) [10] (Zhang *et al*., 2018) [11] (Nguyen *et al*., 2021) [13]. This capability is particularly valuable for diseases such as late blight, where the interval between initial infection and rapid epidemic spread is narrow, making early intervention disproportionately impactful relative to the same intervention applied after visible symptom onset (Singh *et al*., 2020) [12]. Nonetheless, the higher instrumentation and computational cost associated with hyperspectral systems, as reflected in Table 6, indicates that multispectral imaging may represent a more pragmatic option for routine, greenhouse-wide screening in resource-limited protected cultivation enterprises, consistent with prior discussions on the trade-off between spectral resolution and deployment cost in precision agriculture (Wang *et al*., 2017) [9] (Wei *et al*., 2021) [14].

Thermal imaging's comparatively strong performance for Fusarium wilt detection is consistent with the physiological basis of this disease, wherein vascular colonization disrupts water transport and stomatal regulation, producing detectable canopy temperature anomalies prior to visible wilting. This finding echoes previous observations that thermal sensing is particularly well suited to diseases and stresses with a pronounced transpirational component, complementing spectral reflectance-based approaches that are more sensitive to pigment and structural changes (Khasawneh *et al*., 2022) [7] (Jelali, 2024) [8].

The integration of IoT-based environmental monitoring with imaging-derived disease alerts, as implemented in the present framework, reflects an increasingly emphasized direction in smart greenhouse research, wherein microclimatic data streams contextualize and improve the reliability of disease risk prediction beyond what imaging alone can achieve (Abdulridha *et al*., 2020) [15] (De Vijver *et al*., 2020) [16] (Li *et al*., 2019) [17]. By linking leaf wetness duration and humidity patterns to disease-conducive periods, the decision-support system moves toward proactive, epidemiologically informed management rather than purely reactive symptom-triggered response, a direction advocated in recent smart farming literature (De Vijver *et al*., 2020) [16] (Li *et al*., 2019) [17].

From a sustainability perspective, the substantial reduction in labor requirement (~62%) and the associated potential for more judicious, condition-specific agrochemical application support the broader argument that precision digital phenotyping technologies can contribute to reduced pesticide and fungicide overuse, a concern repeatedly raised in discussions of smallholder disease management practices that often default to prophylactic chemical application in the absence of reliable early diagnostics (Fuentes *et al*., 2017) [3]. Earlier detection, by enabling spot-treatment rather than whole-crop spraying, offers a plausible pathway toward more environmentally sustainable protected cultivation.

Several limitations of the present study warrant acknowledgment. The trial was conducted within a single protected cultivation structure and cropping cycle, and while disease pressure was deliberately diversified through supplemented inoculation, the generalizability of classification performance to other greenhouse designs, geographic regions, and pathogen strains requires further validation. The machine vision framework's performance may also be sensitive to variation in canopy architecture, cultivar-specific leaf morphology, and lighting heterogeneity encountered in commercial-scale operations, factors that have been noted as challenges for translating laboratory-trained models to real-world field datasets (Liakos *et al*., 2018) [5]. Additionally, the relatively high cost and technical complexity of hyperspectral systems may constrain near-term adoption among smallholder protected cultivation operators, suggesting that tiered deployment strategies, combining low-cost RGB or multispectral systems for routine monitoring with periodic hyperspectral or thermal screening for high-value or high-risk periods, may offer a more accessible adoption pathway.

Future research should prioritize multi-site, multi-season validation across diverse protected cultivation typologies and pathogen complexes, development of lightweight and edge-deployable models suitable for low-connectivity rural settings, and deeper integration of disease detection outputs with automated actuation systems for irrigation, ventilation, and localized treatment application. Expanding digital phenotyping datasets to include a broader range of tomato cultivars, disease severities, and co-occurring abiotic stresses would further strengthen model robustness and support the transition of these systems from research demonstrations toward routine commercial deployment.

5. Conclusion

In this study, an integrated digital phenotyping and machine vision framework that used RGB, multispectral, hyperspectral, and thermal imaging along with IoT (Internet of Things) environmental monitoring was established, which enabled fast, precise, and non-destructive detection of critical tomato diseases in protected environments. The system gave an overall accuracy of classification of 96.4% and was able to recognize diseases significantly earlier than the traditional visual diagnosis, while also minimizing labor costs. Hyperspectral imaging proved to be the most sensitive technique for diagnosing the disease prior to symptom appearance, while both multispectral and RGB imaging proved to be more cost-efficient means for regular monitoring and screening of crops, which indicates that different types of deployments should be used considering different efficiencies of the technologies. Digital phenotyping and machine vision offer excellent potential in improving precision in plant disease management and in making the process of growing tomatoes more sustainable.

References

1. Mohanty SP, Hughes DP, Salathé M. Using deep learning for image-based plant disease detection. Frontiers in Plant Science. c2016;7:1419.

2. Ferentinos KP. Deep learning models for plant disease detection and diagnosis. Computers and Electronics in Agriculture. 2018;145:311-318.
3. Fuentes A, Yoon S, Kim SC, Park DS. A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition. Sensors. 2017;17(9):2022.
4. Kamilaris A, Prenafeta-Boldú FX. Deep learning in agriculture: a survey. Computers and Electronics in Agriculture. c2018;147:70-90.
5. Liakos KG, Busato P, Moshou D, Pearson S, Bochtis D. Machine learning in agriculture: a review. Sensors. 2018;18(8):2674.
6. Shoaib M, Hussain T, Shah B, Ullah I, Shah SM, Ali F, *et al*. Deep learning-based segmentation and classification of leaf images for detection of tomato plant disease. Frontiers in Plant Science. 2022;13:1031748.
7. Khasawneh N, Faouri E, Fraiwan M. Automatic detection of tomato diseases using deep transfer learning. Applied Sciences. 2022;12(17):8467.
8. Jelali M. Deep learning networks-based tomato disease and pest detection: a first review of research studies using real field datasets. Frontiers in Plant Science. 2024;15:1493322.
9. Wang G, Sun Y, Wang J. Automatic image-based plant disease severity estimation using deep learning. Computational Intelligence and Neuroscience. 2017;2917536.
10. Mahlein AK. Plant disease detection by imaging sensors: parallels and specific demands for precision agriculture and plant phenotyping. Plant Disease. 2016;100(2):241-251.
11. Zhang Y, Chen S, Wang S, Zhang J, Feng L. Imaging technologies for plant high-throughput phenotyping: a review. Frontiers of Agricultural Science and Engineering. 2018;5(4):406-419.
12. Singh V, Sharma N, Singh S. A review of imaging techniques for plant disease detection. Artificial Intelligence in Agriculture. 2020;4:229-242.
13. Nguyen C, Sagan V, Maimaitiyiming M, Maimaitijiang M, Bhadra S, Kwasniewski MT. Early detection of plant viral disease using hyperspectral imaging and deep learning. Sensors. 2021;21(3):742.
14. Wei X, Johnson MA, Langston DB Jr, Mehl HL, Li S. Identifying optimal wavelengths as disease signatures using hyperspectral sensor and machine learning. Remote Sensing. 2021;13(14):2833.
15. Abdulridha J, Ampatzidis Y, Kakarla SC, Roberts P. Detection of target spot and bacterial spot diseases in tomato using UAV-based and benchtop-based hyperspectral imaging techniques. Precision Agriculture. 2020;21(5):955-978.
16. De Vijver R, Mertens K, Heungens K, Somers B, Nuyttens D, Borra-Serrano I, *et al*. In-field detection of *Alternaria solani* in potato crops using hyperspectral imaging. Computers and Electronics in Agriculture. 2020;168:105106.
17. Li Z, Paul R, Tis TB, Saville AC, Hansel JC, Yu T, *et al*. Non-invasive plant disease diagnostics enabled by smartphone-based fingerprinting of leaf volatiles. Nature Plants. 2019;5(8):856-866.
18. Maraveas C, Piromalis D, Arvanitis KG, Bartzanas T, Loukatos D. Applications of IoT for optimized greenhouse environment and resources management. Computers and Electronics in Agriculture. 2022;198:106993.
19. Dhanaraju M, Chenniappan P, Ramalingam K, Pazhanivelan S, Kaliaperumal R. Smart farming: Internet of Things (IoT)-based sustainable agriculture. Agriculture. 2022;12(10):1745.
20. Rehman A, Saba T, Kashif M, Fati SM, Bahaj SA, Chaudhry H. A revisit of internet of things technologies for monitoring and control strategies in smart agriculture. Agronomy. 2022;12(1):127.
21. Food and Agriculture Organization of the United Nations. FAOSTAT statistical database: crops and livestock products. Rome: FAO;. Available from: https://www.fao.org/faostat.