IoT-Enabled Smart Horticulture: Integrating Image Processing for Real-Time Environmental Monitoring and Disease Detection

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Abstract: Traditional horticulture continues to suffer from inefficiencies due to its dependence on manual monitoring, delayed identification of plant diseases, and excessive use of resources, which collectively reduce productivity and increase operational costs. To address these challenges, this research introduces an integrated framework that combines IoT-based multi-sensor monitoring with image processing supported by edge-level CNN-based disease detection and a cloud-enabled decision support system. Experimental validation demonstrates notable outcomes, including 94.2% disease detection accuracy, a 32% reduction in water usage, a 35% decrease in pesticide consumption, and a 22% improvement in crop yield under controlled greenhouse conditions. Owing to its scalability and practicality, the proposed system can be effectively deployed in greenhouses, polyhouses, and open-field horticultural environments to facilitate precision agriculture, optimise resource utilisation, and support sustainable crop management.

Keywords: Smart horticulture; IoT; Image processing; Disease detection; Environmental monitoring; Precision agriculture; CNN; Sensor networks.

Introduction

The global horticulture sector is pivotal for food security, contributing significantly to nutrition and economic stability. However, it remains vulnerable to environmental fluctuations, pest infestations, and diseases, which collectively account for approximately 35% of annual crop losses worldwide. Conventional farming practices rely on periodic manual inspections, which are labor-intensive, subjective, and often reactive rather than preventive. The advent of Industry 4.0 technologies, particularly the Internet of Things (IoT) and artificial intelligence (AI), offers transformative potential for precision horticulture. IoT facilitates real-time, granular monitoring of microclimatic parameters, while image processing enables non-invasive, automated plant health assessment. This paper presents a holistic, scalable system that integrates multi-modal sensor data with deep learning-based visual analytics to enable proactive horticultural management. The proposed framework not only detects anomalies early but also automates irrigation, fertilization, and alert generation, thereby enhancing productivity, sustainability, and resilience.
Related work
Recent years have witnessed growing interest in smart agriculture solutions. Early systems focused primarily on IoT-based soil and weather monitoring without visual analytics. For instance, Li et al. [1] developed a wireless sensor network for soil moisture and temperature tracking but lacked image-based disease detection capabilities. Patil et al. [2] combined basic image processing with IoT for leaf disease

identification but achieved only 88% accuracy and offered no real-time control mechanisms. Sharma et al. [3] advanced the field by integrating IoT with a CNN model, attaining 91% accuracy and basic automation features. However, their system was limited by high computational latency and poor scalability. Other studies have explored drone-based imaging and multispectral analysis but at prohibitive costs for small-scale horticulturists. Table 1 provides a comparative analysis of recent works, highlighting the novelty of our approach in terms of accuracy, real-time responsiveness, cost-effectiveness, and integration depth.

Table 1. Comparative analysis of related works in smart agriculture and horticulture

Study	IoT Sensors	Image Processing	Real-Time Control	Disease Detection Accuracy	Scalability	Cost-Effectiveness
Li et al. [1] (2020)	Yes	No	No	-	Medium	High
Patil et al. [2] (2019)	Yes	Yes (SVM)	No	88.0%	Low	Medium
Sharma et al. [3] (2021)	Yes	Yes (CNN)	Yes	91.0%	Medium	Low
Chen & Wang [4] (2022)	Yes	Yes (Drone-based)	Yes	92.5%	High	Low
This work (2025)	Yes	Yes (CNN+ResNet)	Yes	94.2%	High	High

Key Contribution

This research makes the following key contributions to the field of smart horticulture:

1. Design and implementation of a low-cost, multi-sensor IoT network capable of monitoring soil moisture, temperature, humidity, pH, light intensity, and CO_2 levels with 95% data transmission reliability.
2. Development of a hybrid image processing pipeline combining traditional computer vision techniques (Otsu thresholding, HSV segmentation) with a fine-tuned ResNet-50 CNN model for early and accurate detection of common horticultural diseases (e.g., powdery mildew, leaf blight, bacterial spot).
3. Integration of sensor and image data into a unified cloud-based decision support system that provides real-time alerts, automated irrigation scheduling, and nutrient recommendation reports via a responsive web dashboard.
4. Comprehensive field validation over 120 days in a tomato greenhouse, demonstrating statistically significant improvements in yield, resource efficiency, and disease management compared to conventional methods.

Method, Experiments and Results

System Architecture

The proposed system is structured into three layers: perception, edge, and cloud. The perception layer comprises wireless sensor nodes (ESP32-based) equipped with DHT22 (temperature/humidity), capacitive soil moisture sensors, pH sensors, BH1750 (light), and MQ-135 (air quality). Each node transmits data via

LoRaWAN to an edge gateway (Raspberry Pi 4). A 12 MP Raspberry Pi camera module captures plant images at scheduled intervals. The edge layer performs initial image preprocessing and runs a lightweight CNN model for real-time inference. The cloud layer (AWS IoT Core) aggregates data, hosts a deeper ResNet-50 model for detailed analysis, and manages the user dashboard.

Image Processing and Disease Detection Pipeline

The image analysis follows a four-stage pipeline:

1. Preprocessing: Images are resized to 224×224, converted to HSV colour space, and subjected to histogram equalisation.
2. Segmentation: Otsu's method and k-means clustering isolate leaf regions from the background.
3. Feature Extraction: A pre-trained ResNet-50 extracts 2048-dimensional feature vectors.
4. Classification: A fully connected neural network with dropout (0.5) and softmax output classifies leaves into: Healthy, Powdery Mildew, Early Blight, Late Blight, or Bacterial Spot.

The model was trained on 8,000 labelled images from the PlantVillage dataset and augmented with 2,000 locally captured images. Data augmentation included rotation, flipping, and brightness adjustment.

Experimental Setup

The system was deployed in a 0.5-acre greenhouse cultivating tomatoes (Solanum lycopersicum) in Tamil Nadu, India, from January to April 2025. The greenhouse was divided into two sections: an experimental zone (IoT-enabled) and a control zone (traditional farming). Both zones followed identical planting patterns, irrigation schedules (initially), and pest management protocols. Data was collected every 10 minutes from sensors and daily from cameras.

Table 2. Sensor specifications and measurement ranges

Sensor	Parameter	Range	Accuracy	Sampling Interval
DHT22	Temperature	-40°C to 80°C	±0.5°C	10 min
DHT22	Humidity	0–100% RH	±2%	10 min
Capacitive Soil Moisture	Soil Moisture	0–100% VWC	±3%	10 min
pH Sensor (Analog)	Soil pH	0–14	±0.1	60 min
BH1750	Light Intensity	0–65535 lux	±10%	10 min
MQ-135	CO_2	10–1000 ppm	±15%	30 min

Results

Disease Detection Performance: The hybrid CNN model achieved an overall accuracy of 94.2%, with precision and recall scores as detailed in Table 3.

Table 3. Disease detection performance metrics (confusion matrix derived)

Class	Precision	Recall	F1-Score	Support (Images)
Healthy	0.96	0.95	0.955	450
Powdery Mildew	0.93	0.94	0.935	420
Early Blight	0.94	0.92	0.930	400
Late Blight	0.95	0.96	0.955	380
Bacterial Spot	0.92	0.94	0.930	350
Weighted Avg	0.94	0.94	0.942	2000

Resource Optimisation: The IoT-enabled section demonstrated significant savings (Table 4).

Table 4. Resource usage comparison: IoT vs. Traditional section (120-day period)

Resource	IoT Section	Traditional Section	Reduction
Water (liters)	12,500	18,400	32.1%
Fertilizer (kg)	45	62	27.4%
Pesticide (liters)	8.2	12.6	34.9%
Energy (kWh)	210	290	27.6%

Yield and Quality Improvement: The experimental zone yielded 3.8 kg per plant compared to 3.1 kg in the control zone—a 22.6% increase. Fruit quality (measured by brix level and visual grading) was also superior in the IoT section.

Discussions

The results validate the efficacy of integrating IoT and image processing for precision horticulture. The high disease detection accuracy (94.2%) outperforms previous studies, primarily due to the hybrid model combining traditional segmentation with deep learning. The resource savings align with global sustainability goals, demonstrating that smart technology can reduce water and chemical usage without compromising yield. The real-time alert system enabled early interventions, reducing disease spread by 40% compared to the control section.

However, challenges were encountered:

1. Sensor calibration drifts over time, requiring weekly recalibration.
2. Image occlusion due to leaf overlap, which occasionally led to false negatives.
3. Initial setup cost (~$500 per 0.1 acre), which may be prohibitive for small farmers without subsidies.

Future work will focus on:

•Incorporating drone-based multispectral imaging for larger areas.

•Using blockchain for secure, transparent data logging and supply chain integration.

•Developing a mobile app with offline inference capabilities for regions with poor internet connectivity.

Conclusions

The study addresses the limitations of conventional horticultural practices, which rely heavily on manual monitoring, often resulting in delayed disease identification and unnecessary resource consumption. To overcome these challenges, a multi-layer IoT framework was implemented, integrating hybrid image processing techniques that combine CNN-based deep learning with traditional computer vision methods, supported by a cloud-enabled decision support system. Experimental evaluation demonstrated highly encouraging outcomes, including 94.2% accuracy in disease detection, a 32% reduction in water usage, a 35% decrease in pesticide consumption, and a 22.6% improvement in crop yield. Despite its strong performance, the system requires periodic sensor calibration and involves initial setup costs; future enhancements will focus on incorporating drone-based imaging and blockchain technologies to further improve scalability, reliability, and data security.

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