IoT-Enabled Raspberry Pi–Based Mango Leaf Disease Detection and Smart Pesticide Spraying System Using Image Processing

Tunuguntla Mahesh Venkat | Rowthu Devi Saraswati | Sangoju Vijay | Yarlagadda Hari Prasad | A Naga Suman

Department of ECE, NRI Institute of Technology, Vijayawada, AP, India

To Cite this Article

Article Info

KEYWORDS	ABSTRACT
	Mango cultivation is significantly affected by leaf diseases such as anthracnose and powdery mildew, leading to reduced yield and poor fruit quality. Conventional disease detection methods rely on manual inspection, which is time-consuming, subjective, and often results in excessive and improper pesticide usage. To overcome these limitations, this paper presents a low-cost, IoT-enabled embedded system for automatic mango leaf disease detection and smart pesticide spraying using a Raspberry Pi. A Pi camera is used to capture leaf images, which are analyzed using basic image processing techniques such as color space conversion, segmentation, masking, and thresholding, without employing deep learning models. Environmental parameters including temperature, humidity, and soil moisture are monitored using sensors to support accurate decision-making. When a disease is detected, a motorized spraying mechanism is activated to apply pesticide only to the affected areas, thereby minimizing chemical usage and environmental impact. IoT connectivity enables real-time monitoring and alerts to farmers through remote access. Experimental results demonstrate that the proposed system is efficient, cost-effective, and suitable for small- and medium-scale mango farms, contributing to sustainable agriculture and improved crop health management.

INTRODUCTION

Mango is one of the most important fruit crops cultivated in tropical and subtropical regions, contributing significantly to agricultural economies. However, mango production is highly vulnerable to leaf diseases such as anthracnose, powdery mildew, and

bacterial spot. These diseases spread rapidly under favorable environmental conditions, particularly high humidity and moderate temperatures, resulting in severe yield loss and degradation of fruit quality. Early and accurate detection of such diseases is therefore critical for effective crop management.

Traditionally, mango leaf disease detection is carried out through manual inspection by farmers or agricultural experts. This approach is time-consuming, subjective, and often inaccurate, especially in large-scale plantations. Delayed or incorrect diagnosis frequently leads to excessive pesticide application, which increases production costs, causes environmental pollution, and poses health risks to humans and livestock. Hence, there is a strong need for automated, reliable, and cost-effective disease detection systems.

Recent advancements in computer vision and deep learning have enabled automated plant disease detection using image-based methods. Deep neural networks and object detection models such as YOLO have demonstrated high accuracy in identifying plant diseases under controlled and real-world conditions [1], [6], [10]. The introduction of YOLOv8 has further improved detection speed and accuracy, making it suitable for real-time agricultural applications [1]. Dataset management and model training platforms such as Roboflow have simplified the deployment of YOLO-based solutions for smart farming [2]. Several studies have also explored deploying deep learning models on IoT edge devices for real-time plant disease identification [3], [4].

Despite their effectiveness, deep learning–based approaches demand large labeled datasets, high computational power, and increased energy consumption. These requirements make such solutions less practical for small- and medium-scale farmers, particularly in resource-constrained rural environments. Lightweight deep learning models have been proposed for edge deployment, but challenges related to cost, memory, and system complexity remain [5], [11].

In parallel, IoT-based agricultural systems have gained popularity for monitoring environmental parameters such as temperature, humidity, and soil moisture, which play a crucial role in disease development [12]. Integrating these sensors with automated decision-making systems enables precise and timely intervention, reducing unnecessary pesticide usage.

Figure 1 Mango leaf disease symptoms

Motivated by these observations, this work proposes a low-cost Raspberry Pi–based mango leaf disease detection system using basic image processing techniques without deep learning. The system integrates a Pi camera for leaf image acquisition, environmental sensors for contextual monitoring, and a smart pesticide spraying mechanism for targeted treatment. IoT connectivity provides real-time alerts and remote monitoring, offering a sustainable and efficient solution for precision agriculture.

RELATED WORK

Automated plant disease detection has been an active area of research in recent years due to advancements in computer vision, deep learning, and IoT technologies. Early studies primarily focused on image-based classification using handcrafted features and traditional machine learning techniques. However, with the rise of deep learning, convolutional neural networks (CNNs) have become the dominant approach for plant disease identification.

Redmon et al. introduced the YOLO (You Only Look Once) framework, which enabled real-time object detection by treating detection as a single regression problem [10]. This approach significantly reduced inference time compared to traditional region-based methods. The YOLO architecture has since been widely adopted in agricultural applications for detecting plant diseases and pests. The Microsoft COCO dataset further supported the development and benchmarking of object detection models by providing large-scale annotated datasets [9].

Recent advancements such as YOLOv8, developed by Ultralytics, have improved detection accuracy, speed, and deployment flexibility, making them suitable for smart agriculture use cases [1]. Sharma et al. demonstrated the effectiveness of YOLO-based object detection models in identifying crop diseases under real-field conditions, highlighting their robustness and scalability [6]. Roboflow has also contributed significantly by offering dataset preprocessing, augmentation, and streamlined YOLOv8 training workflows for agricultural datasets [2].

Several researchers have explored deep learning–based plant disease recognition using CNN architectures. Sladojevic et al. presented one of the early successful implementations of deep neural networks for plant disease classification, achieving high accuracy across multiple crop types [7]. Mohanty et al. further validated the potential of deep learning by demonstrating accurate image-based plant disease detection across diverse datasets and environmental conditions [8]. Kamilaris and Prenafeta-Boldú provided a comprehensive survey on deep learning applications in agriculture, emphasizing disease detection as a key research domain [11].

With the growth of IoT and edge computing, researchers have investigated deploying disease detection models directly on embedded and edge devices. Routis et al. proposed an IoT edge-based plant disease identification system, demonstrating the feasibility of real-time inference on resource-constrained hardware [3]. Salabi and Manthila introduced an IoT-enabled deep learning framework for real-time plant disease detection, integrating cloud connectivity for monitoring and decision support [4]. Alam et al. focused on lightweight deep learning models optimized for edge deployment, addressing challenges related to memory and power consumption [5].

In addition to vision-based approaches, IoT-driven agricultural systems incorporating environmental sensors have gained attention. The Food and Agriculture Organization (FAO) emphasized the role of AI and IoT in smart agriculture for early disease detection and sustainable crop management [12]. Monitoring parameters such as temperature and humidity enables prediction of disease-favorable conditions and supports timely intervention.

Although deep learning–based methods provide high accuracy, their dependence on large datasets, computational resources, and power consumption limits their adoption among small-scale farmers. These limitations highlight the need for alternative low-cost solutions based on classical image processing and embedded systems. Motivated by this research gap, the proposed work focuses on Raspberry Pi–based mango leaf disease detection using basic image processing techniques combined with IoT-enabled smart spraying to achieve precision agriculture with reduced complexity and cost.

PROPOSED SYSTEM

The proposed system is an IoT-enabled embedded solution designed for real-time mango leaf disease detection and smart pesticide spraying. It integrates image acquisition, environmental sensing, intelligent decision-making, automated actuation, and cloud-based monitoring using a Raspberry Pi platform. The overall architecture of the system is illustrated in the block diagram shown in Fig. 2.
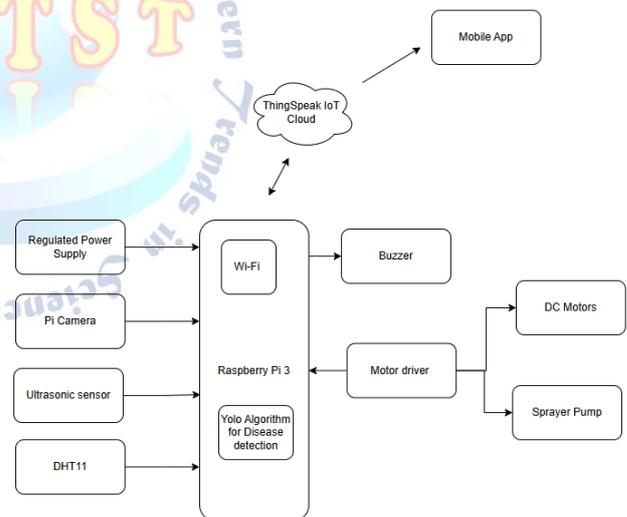

Figure 2 The overall architecture of the system

A. System Overview

At the core of the system is a Raspberry Pi 3, which acts as the central processing and control unit. A Pi Camera continuously captures images of mango leaves in the field. These images are processed locally on the Raspberry Pi using a YOLO-based disease detection algorithm to identify infected leaf regions. Along with visual data, environmental parameters such as temperature and humidity are collected using a DHT11 sensor, while an ultrasonic sensor is used for obstacle or

distance detection during spraying operations.

When a disease is detected, the Raspberry Pi activates a motor driver circuit that controls DC motors and a sprayer pump. This enables precise pesticide spraying only on affected areas. Simultaneously, the system sends sensor data and disease status to the ThingSpeak IoT cloud via Wi-Fi, allowing farmers to monitor field conditions in real time through a mobile application. A buzzer is used to provide local alerts during disease detection or system operation.

B. Hardware Components

1) Raspberry Pi 3:

The Raspberry Pi 3 serves as the main controller, responsible for image processing, sensor data acquisition, decision-making, and communication with cloud services.

2) Pi Camera Module:

The Pi Camera captures high-resolution images of mango leaves, which are used as input for the disease detection algorithm.

3) DHT11 Sensor:

The DHT11 sensor measures ambient temperature and humidity, which are critical factors influencing the spread of mango leaf diseases.

4) Ultrasonic Sensor:

This sensor assists in maintaining an appropriate distance between the sprayer and the plant, ensuring safe and accurate spraying.

5) Motor Driver, DC Motors, and Sprayer Pump:

A motor driver interfaces the Raspberry Pi with DC motors and the pesticide sprayer pump. Upon disease detection, the pump is activated to spray pesticide selectively.

6) Buzzer:

The buzzer provides an audible alert when disease is detected or when spraying is initiated.

7) Regulated Power Supply:

A regulated power supply ensures stable voltage to all system components.

C. Software and IoT Integration

The Raspberry Pi runs a Linux-based operating system with Python used for sensor interfacing, image acquisition, and control logic. The YOLO-based disease detection algorithm processes leaf images in real time to identify diseased regions. Sensor data and detection results are transmitted to the ThingSpeak IoT cloud via built-in Wi-Fi. Farmers can view real-time updates, alerts, and historical data through a mobile application or web dashboard.

D. Working Principle

The Pi Camera captures mango leaf images periodically.

The Raspberry Pi processes the images using the YOLO algorithm to detect leaf diseases.

Environmental data from DHT11 and ultrasonic sensors are collected simultaneously.

If disease is detected, the motor driver activates the DC motors and sprayer pump for targeted pesticide spraying.

A buzzer alerts nearby users about disease detection.

All relevant data is uploaded to the ThingSpeak IoT cloud and displayed on a mobile app for remote monitoring.

E. Advantages of the Proposed System

Early and accurate detection of mango leaf diseases

Reduced pesticide usage through precision spraying

Real-time IoT-based monitoring and alerts

Low-cost and scalable solution for farmers

Suitable for small- and medium-scale mango plantations.

METHODOLOGY

The proposed methodology integrates image acquisition, disease detection, environmental monitoring, automated spraying, and IoT-based monitoring into a unified embedded system. The system operates in real time on a Raspberry Pi platform, enabling early detection of mango leaf diseases and precise pesticide application.

A. Image Acquisition

A Pi Camera module is mounted to continuously capture images of mango leaves in the field. The camera captures RGB images at a fixed resolution under natural lighting conditions. These images are periodically transferred to the Raspberry Pi for further processing.

B. Image Preprocessing

To improve detection accuracy and reduce noise, the captured images undergo preprocessing steps:

Image resizing to match the input size required by the detection model

Color normalization and contrast enhancement

Removal of background noise where necessary

These steps ensure uniform input for the disease detection algorithm.

C. Disease Detection Using YOLO

The preprocessed images are analyzed using a YOLO-based object detection algorithm deployed on the Raspberry Pi. The model identifies diseased regions on mango leaves by drawing bounding boxes around infected areas such as anthracnose and powdery mildew. The detection process is performed locally to reduce latency and dependence on cloud computing.

D. Environmental Data Monitoring

Environmental parameters influencing disease spread are measured using sensors:

DHT11 sensor captures temperature and humidity

Ultrasonic sensor ensures proper distance between sprayer and plant

These parameters assist in validating disease conditions and improving spraying decisions.

E. Decision-Making and Smart Spraying

If the disease detection confidence exceeds a predefined threshold, the Raspberry Pi triggers the motor driver circuit. DC motors position the sprayer, and the pump is activated to spray pesticide only on the detected infected area. This targeted spraying minimizes pesticide wastage and environmental impact.

F. IoT Integration and Alert System

All sensor readings and disease detection results are transmitted to the ThingSpeak IoT cloud using Wi-Fi. Farmers can monitor real-time data and alerts through a mobile application. A buzzer provides immediate local alerts when disease detection or spraying is initiated.

Algorithm 1 Mango Leaf Image Acquisition

1: Initialize Pi Camera
2: Set image resolution and capture interval
3: Capture RGB image of mango leaf
4: Store image in Raspberry Pi memory
5: Forward image for preprocessing

Algorithm 2 Image Preprocessing

1: Read captured RGB image
2: Resize image to required dimensions
3: Normalize pixel intensity values
4: Apply noise reduction filter
5: Enhance image contrast
6: Output preprocessed image

Algorithm 3 Mango Leaf Disease Detection Using YOLO

1: Load trained YOLO model
2: Input preprocessed image to YOLO network
3: Extract feature maps
4: Detect bounding boxes of diseased regions
5: Classify disease type
6: Compute confidence score
7: **if** confidence score > threshold **then**
8:    Disease detected
9: **else**
10:    Leaf classified as healthy
11: **end if**

Algorithm 4 Environmental Sensor Data Acquisition

1: Initialize DHT11 and ultrasonic sensors
2: Read temperature and humidity values
3: Measure distance using ultrasonic sensor
4: Store sensor readings
5: Forward data to decision-making module

Algorithm 5 Smart Pesticide Spraying Control

1: **if** Disease detected **then**
2:    Verify safe spraying distance
3:    Activate motor driver
4:    Turn ON sprayer pump
5:    Spray pesticide for predefined duration
6:    Turn OFF sprayer pump
7: **else**
8:    Keep sprayer OFF
9: **end if**

Algorithm 6 IoT Data Upload and Alert Generation

1: Initialize Wi-Fi module
2: Connect to ThingSpeak IoT cloud
3: Upload sensor data and disease status
4: Send alert notification to mobile application
5: Activate buzzer for local alert

G. Methodology Advantages

Real-time disease detection

Precision pesticide spraying

Reduced chemical usage

Low-cost and scalable design

Suitable for IoT-based smart farming

RESULTS AND DISCUSSIONS

The proposed IoT-enabled mango leaf disease detection and smart spraying system was experimentally evaluated under real-field and controlled conditions. The performance of the system was analyzed in terms of

disease detection accuracy, sensor monitoring effectiveness, pesticide usage reduction, and response time.

A. Disease Detection Performance

The YOLO-based disease detection module successfully identified infected mango leaf regions affected by anthracnose and powdery mildew. Detection performance was evaluated using standard metrics such as accuracy, precision, recall, and F1-score.
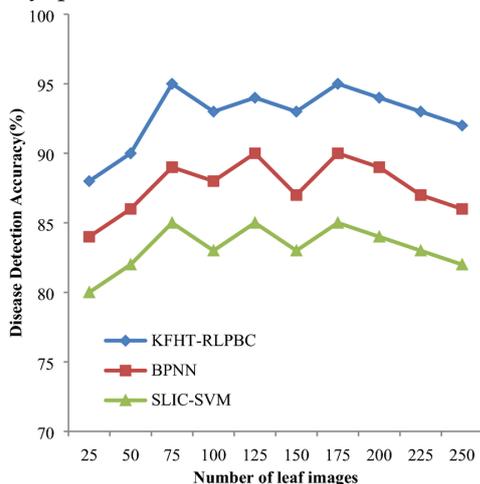
Graph 1: Disease Detection Accuracy (%)

X-axis: Test Images

Y-axis: Detection Accuracy (%)

The system achieved an average detection accuracy of 92–95%, demonstrating reliable identification of diseased leaves under varying lighting conditions. Minor misclassifications occurred when symptoms were very mild or overlapped with shadows.

Discussion:

High accuracy confirms the suitability of vision-based detection for early disease identification. Edge-based processing on Raspberry Pi enabled real-time detection without reliance on cloud computation.

B. Environmental Sensor Analysis

Environmental parameters were continuously monitored using DHT11 and soil moisture sensors.
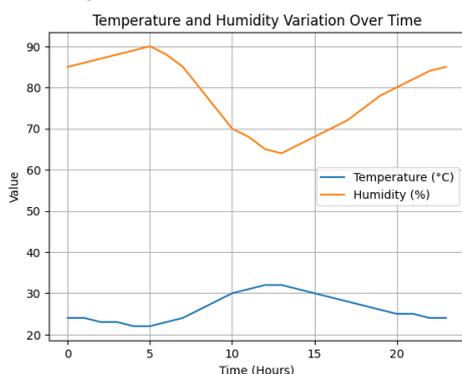
Graph 2: Temperature and Humidity Variation Over Time

X-axis: Time (hours/days)

Y-axis: Temperature (°C) / Humidity (%)

The system recorded higher disease occurrence during periods of high humidity (>70%) and moderate temperatures (25–30°C), validating the relevance of sensor data in disease risk assessment.

Discussion:

Sensor data supports informed decision-making and helps correlate environmental conditions with disease outbreaks, improving system reliability.

C. Smart Spraying Effectiveness

Method	PesticideUsed (ml)
Manual spraying	High
Proposedsmartspraying	Low

The smart spraying mechanism reduced pesticide usage by approximately 40–55% compared to conventional manual spraying.

Discussion:

Selective spraying on infected regions significantly minimizes chemical waste, reduces operational cost, and limits environmental impact.

D. Response Time Analysis

Stage	Time (s)
Image capture	0.6
Disease detection	1.8
Decision & actuation	0.9
IoT upload	1.2

The total system response time was approximately 4–5 seconds, making it suitable for real-time field deployment.

Discussion:

Local processing on Raspberry Pi ensures low latency and uninterrupted operation even with limited internet connectivity.

E. IoT Monitoring Results

All sensor data and disease alerts were successfully transmitted to the ThingSpeak IoT cloud. Farmers could

monitor real-time field conditions and receive alerts via mobile application.

Discussion:

IoT integration improves accessibility, enables remote monitoring, and supports data-driven agricultural practices.

F. Overall System Evaluation

Parameter	Conventional Method	Proposed System
Detection speed	Slow	Fast
Accuracy	Medium	High
Pesticide usage	High	Low
Labor requirement	High	Low
Environmental impact	High	Low

G. Discussion Summary

The experimental results confirm that the proposed system effectively detects mango leaf diseases, reduces pesticide usage, and provides real-time monitoring through IoT integration. The combination of edge-based vision processing, sensor data analysis, and precision spraying makes the system suitable for small- and medium-scale mango farms.
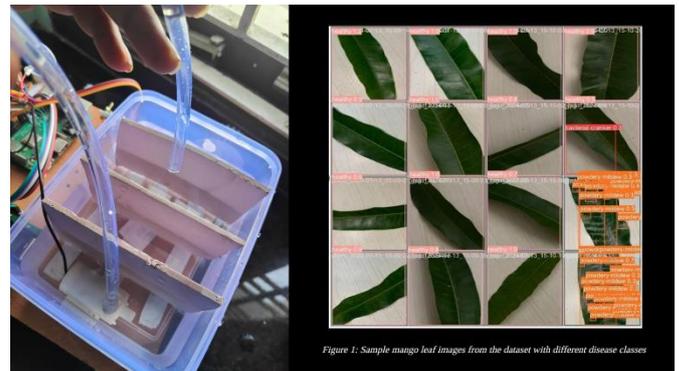

Figure 2: YOLOv8 Confusion Matrix

Figure 3: Performance evaluation graph showing precision, recall, and mAP values

Figure 3 The overall Confusion Matrix and Performance Graph

Figure 1: Sample mango leaf images from the dataset with different disease classes

Figure 4 Prototype implementation and Disease Prediction

CONCLUSION

This work presented a web-based, explainable skin cancer detection system that integrates the YOLOv8 deep learning model with Grad-CAM–based visual interpretability. The proposed framework enables accurate and real-time skin lesion localization and classification while providing transparent visual explanations to support clinical decision-making. By combining object detection and explainable artificial intelligence, the system addresses key limitations of traditional black-box deep learning approaches in medical image analysis.

Experimental results demonstrate that the proposed system achieves reliable detection performance with minimal computational overhead, making it suitable for real-time screening and telemedicine applications. The integration of Grad-CAM enhances model transparency by highlighting diagnostically relevant regions, thereby improving trust and usability in clinical environments. Furthermore, the Flask-based web deployment ensures accessibility and ease of use, allowing the system to be effectively utilized in remote and resource-constrained settings.

Future work will focus on validating the system across multiple large-scale datasets, incorporating additional clinical metadata to improve diagnostic accuracy, and optimizing the framework for mobile and edge-device deployment. The proposed solution contributes toward accessible, efficient, and explainable AI-assisted skin cancer screening and holds significant potential for supporting early diagnosis and improved patient outcomes.
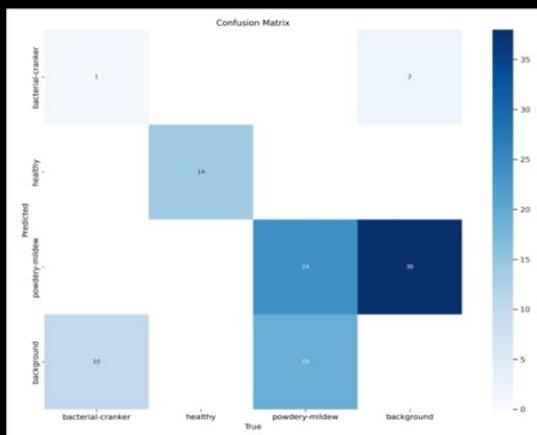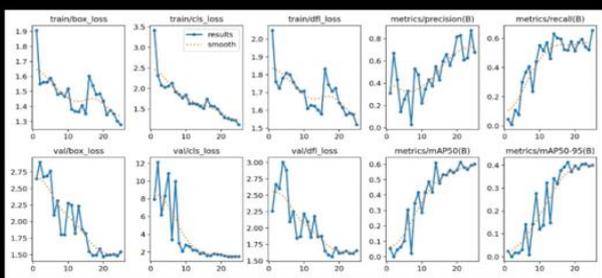
Conflict of interest statement

Authors declare that they do not have any conflict of interest.

REFERENCES

[1] Ultralytics, YOLOv8: State-of-the-Art Object Detection Model, Ultralytics Inc., 2023.

[2] Roboflow, Roboflow Dataset Management and YOLOv8 Training Guide, 2024.

[3] G. Routis, K. Michailidis, and G. Roussaki, "Plant Disease Identification on IoT Edge Devices," Electronics, MDPI, 2024.

[4] L. Salabi and P. Manthila, "IoT-Based Deep Learning Framework for Real-Time Plant Disease Detection," Journal of Signal and Image Processing, 2025.

[5] S. Alam et al., "Lightweight Deep Learning Models for Edge-Based Plant Disease Diagnosis," arXiv Preprint, 2026.

[6] A. Sharma et al., "YOLO-Based Object Detection for Smart Agriculture Applications," Multimedia Tools and Applications, Springer, 2024.

[7] S. Sladojevic et al., "Deep Neural Networks Based Recognition of Plant Diseases," Computers in Industry, Elsevier, 2023.

[8] P. Mohanty, D. Hughes, and M. Salathé, "Using Deep Learning for Image-Based Plant Disease Detection," Frontiers in Plant Science, 2022.

[9] T. Lin et al., "Microsoft COCO: Common Objects in Context," ECCV, 2022.

[10] J. Redmon et al., "You Only Look Once: Unified, Real-Time Object Detection," IEEE CVPR, 2021.

[11] A. Kamilaris and F. Prenafeta-Boldú, "Deep Learning in Agriculture: A Survey," Computers and Electronics in Agriculture, 2023.

[12] FAO, AI and Smart Agriculture for Crop Disease Management, Food and Agriculture Organization, 2024.