

IoT-Based Automatic Cotton Leaf Disease Detection, Infection Percentage Estimation, and Treatment Recommendation Using Raspberry Pi

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Abstract: Cotton is one of the most important commercial crops worldwide, and its productivity is significantly affected by various leaf diseases such as bacterial blight, alter aria leaf spot, Cercospora leaf spot, powdery mildew, and leaf curl disease. Early and accurate identification of these diseases is essential to minimize crop losses and improve yield. Traditional disease diagnosis relies on manual field inspection by experts, which is time-consuming, labour-intensive, and often impractical for large agricultural fields. The proposed system integrates a Raspberry Pi5, a high-resolution camera module, environmental sensors, and wireless communication technologies to create an intelligent crop monitoring platform. Images of cotton leaves are captured using the Raspberry Pi camera and processed through computer vision techniques for leaf segmentation and feature extraction. A lightweight deep learning model based on MobileNetV2 is employed to automatically identify different cotton leaf diseases. In addition to disease classification, image segmentation techniques are used to calculate the percentage of infected leaf area, enabling the system to determine the severity level of infection. The system also collects environmental parameters such as temperature, humidity, soil moisture, and light intensity using IoT sensors. These parameters, along with disease diagnosis results, are transmitted to a cloud-based dashboard for real-time monitoring and analysis. Automated alerts can be sent to farmers through SMS or mobile notifications when severe infections are detected. Experimental evaluation is expected to achieve disease classification accuracy above 93%, infection area estimation error below 5%, and real-time inference within one second per image on the Raspberry Pi platform. The proposed solution offers a cost-effective, portable, and scalable approach for precision agriculture by combining artificial intelligence, image processing, and IoT technologies. The system enables early disease detection, accurate infection assessment, timely treatment recommendations, reduced pesticide usage, and improved cotton crop productivity, making it a valuable tool for smart farming applications.

Keywords: Raspberry Pi, Internet of Things (IoT), Deep Learning, Computer Vision, Infection, MobileNetV2

I. INTRODUCTION

Agriculture plays a vital role in the economy of many countries, providing food, raw materials, and employment opportunities to a large population. Among various cash crops, cotton is one of the most important fibre crops and serves as a major source of income for farmers and industries. Cotton is extensively cultivated for textile production; however, its yield and quality are significantly affected by several plant diseases. Common cotton leaf diseases such as bacterial blight, alter aria leaf spot, Cercospora leaf spot, powdery mildew, and leaf

curl disease can cause severe damage to crops, leading to substantial economic losses. Early detection and proper management of these diseases are therefore essential to ensure healthy crop growth and maximize agricultural productivity.

Traditional disease identification methods rely primarily on manual visual inspection by agricultural experts or farmers. Although effective to some extent, these methods are often time-consuming, labour-intensive, subjective, and prone to human error. Moreover, large agricultural fields make

continuous monitoring difficult, resulting in delayed disease diagnosis and treatment. In many rural areas, access to plant pathology experts is limited, further increasing the risk of disease spread and crop damage. Therefore, there is a growing need for intelligent and automated systems capable of detecting plant diseases accurately and efficiently at an early stage.

Recent advancements in Artificial Intelligence (AI), Computer Vision, Deep Learning, and the Internet of Things (IoT) have created new opportunities for developing smart agricultural solutions. Computer vision techniques can analyse leaf images to identify disease symptoms, while deep learning models can automatically learn complex patterns associated with different plant diseases. Simultaneously, IoT technologies enable real-time monitoring of environmental conditions such as temperature, humidity, soil moisture, and light intensity, which are closely related to disease development and crop health. Integrating these technologies can provide farmers with timely information and decision support for effective crop management.

IoT-Based Automatic Cotton Leaf Disease Detection, Infection Severity Estimation, and Treatment Recommendation System Using Raspberry Pi. The system employs a Raspberry Pi as the central processing unit, connected to a high-resolution camera for capturing cotton leaf images and various sensors for monitoring environmental conditions. Image processing and deep learning algorithms are used to classify cotton leaf diseases automatically. In addition to disease identification, the system estimates the percentage of infected leaf area through image segmentation techniques, allowing accurate assessment of disease severity levels. Based on the detected disease and infection percentage, an intelligent recommendation module suggests suitable treatment measures to farmers.

The collected disease information and environmental parameters are transmitted to a cloud-based IoT platform, enabling remote monitoring through a web or mobile dashboard. The system can also generate alerts when severe infections are detected, helping farmers take timely

preventive actions. By combining disease diagnosis, infection quantification, environmental monitoring, and treatment recommendation into a single platform, the proposed system aims to support precision agriculture practices and improve cotton crop management.

The primary goal of this work is to develop a low-cost, portable, and efficient smart farming solution capable of providing real-time disease detection and decision support directly in agricultural fields. The proposed system is expected to reduce crop losses, minimize excessive pesticide usage, improve treatment effectiveness, and enhance overall cotton production. Furthermore, the adoption of Raspberry Pi-based edge computing ensures fast processing, reduced dependence on cloud resources, and suitability for deployment in rural agricultural environments.

In summary, the integration of IoT, computer vision, and deep learning technologies offers a promising approach for modernizing disease management in cotton cultivation. The proposed system contributes toward sustainable agriculture by enabling early disease detection, accurate infection assessment, informed treatment decisions, and continuous crop health monitoring, thereby supporting higher productivity and improved farmer livelihoods.

II. LITERATURE REVIEW

Recent advances in Artificial Intelligence, Deep Learning, Computer Vision, Edge Computing, and the Internet of Things have transformed agricultural monitoring systems. Researchers have increasingly focused on developing automated plant disease detection systems that provide accurate diagnosis, real-time monitoring, and intelligent decision support. Cotton cultivation, being highly vulnerable to fungal, bacterial, and viral diseases, has benefited significantly from these technologies.

Mohanty et al. (2016) developed a CNN-based plant disease classification model using the PlantVillage dataset containing over 50,000 images from multiple crop species. The study utilized deep neural networks such as AlexNet and GoogleNet and

achieved classification accuracies exceeding 99% under controlled conditions. This work demonstrated the effectiveness of deep learning for agricultural image analysis and established a benchmark for subsequent research.

Jawad et al. (2017) proposed an IoT-based smart agriculture framework using wireless sensor networks to monitor temperature, humidity, and soil moisture. The system improved resource management and supported precision irrigation practices. However, disease diagnosis capabilities were not integrated into the platform.

Ferentinos (2018) investigated several deep learning architectures including VGG16, Alex Net, and Google Net for plant disease recognition. Experimental results showed classification accuracies above 99%, confirming that CNN-based approaches outperform traditional machine learning techniques. However, the computational complexity of large models limited their deployment on resource-constrained embedded devices.

Agarwal et al. (2019) implemented a Raspberry Pi-based crop monitoring system using environmental sensors and image analysis. The study demonstrated that local processing reduced cloud communication overhead and improved response times.

Saranya et al. (2020) applied CNN-based classification techniques for identifying cotton leaf diseases such as bacterial blight and alternaria leaf spot. Their model achieved high classification accuracy and reduced processing time compared to conventional machine learning algorithms. The study highlighted the potential of deep learning for practical disease diagnosis in cotton cultivation.

Mustofa et al. (2023) presented a comprehensive review of deep learning techniques used for plant leaf disease diagnosis. The study compared CNNs, Vision Transformers (ViT), YOLO-based object detectors, and hybrid architectures. The authors concluded that deep learning models consistently outperform traditional machine learning methods in terms of accuracy and robustness. The review also highlighted challenges such as dataset imbalance,

field image variability, and computational requirements for deployment on embedded devices. Nazeer et al. (2024) developed a deep learning framework for detecting susceptibility levels of Cotton Leaf Curl Disease (CLCuD). The proposed model classified disease severity stages and demonstrated high prediction accuracy for disease progression assessment. The study emphasized the importance of severity estimation for effective crop management and early intervention.

Pan et al. (2024) proposed a lightweight YOLOv8-based cotton disease detection model designed for deployment on resource-constrained devices. The model achieved real-time disease detection performance in natural field environments while reducing computational requirements. The study demonstrated that lightweight architectures can maintain high detection accuracy while enabling edge deployment.

Gao et al. (2024) introduced an intelligent cotton pest and disease detection system that integrates Transformer networks and knowledge graphs. The proposed framework improved feature extraction and disease recognition performance compared with conventional CNN-based methods. The study demonstrated the effectiveness of attention mechanisms for agricultural image analysis.

Akbar et al. (2024) developed a deep learning approach for automatic lesion detection in cotton leaf images. The model localized infected regions and accurately identified lesion boundaries. The proposed system improved disease severity estimation by measuring affected leaf regions directly from field images.

Feng et al. (2024) developed a Raspberry Pi-based deep learning system for cotton whitefly detection and counting. The system performed image acquisition, pest detection, and population estimation directly on Raspberry Pi hardware. Results demonstrated that edge computing platforms can effectively support agricultural monitoring applications while maintaining low deployment costs.

Salka et al. (2025) published an extensive review of CNN-based plant disease detection systems. The review analysed current deep learning architectures, datasets, evaluation metrics, and deployment strategies. The authors concluded that Mobile Net, Efficient Net, YOLO, and Vision Transformers represent the most promising solutions for practical agricultural disease detection systems

III. METHODOLOGY

The proposed system aims to automatically detect cotton leaf diseases, estimate the percentage of infection on the leaf surface, classify disease severity, and recommend appropriate treatment using a Raspberry Pi-based IoT platform. The methodology integrates image acquisition, image pre-processing, deep learning-based disease classification, infection severity estimation, environmental monitoring, and cloud-based data communication. The complete workflow enables real-time monitoring and intelligent decision-making for precision agriculture applications.

1. System Methodology Flowchart

The proposed system is designed to automatically detect cotton leaf diseases, estimate the percentage of infection, classify disease severity, and recommend suitable treatment using Raspberry Pi and IoT technologies. The methodology begins with system initialization, where the Raspberry Pi, camera module, sensors, and communication modules are activated and configured for operation.

In the image acquisition stage, the Raspberry Pi Camera Module captures high-resolution images of cotton leaves from the field. Simultaneously, environmental data such as temperature, humidity, soil moisture, light intensity, and GPS location are collected through connected sensors. These environmental parameters provide additional information regarding crop health and disease development conditions.

The captured leaf image then undergoes image pre-processing to improve image quality and enhance disease features. Pre-processing operations include image resizing, noise removal, color space

conversion, contrast enhancement, and normalization. These techniques help reduce unwanted variations and improve the accuracy of subsequent analysis.

After pre-processing, leaf segmentation is performed to separate the leaf from the background. This step extracts only the leaf region and eliminates irrelevant objects from the image. The segmented leaf image is then provided as input to the MobileNetV2 Convolutional Neural Network (CNN) model for disease classification.

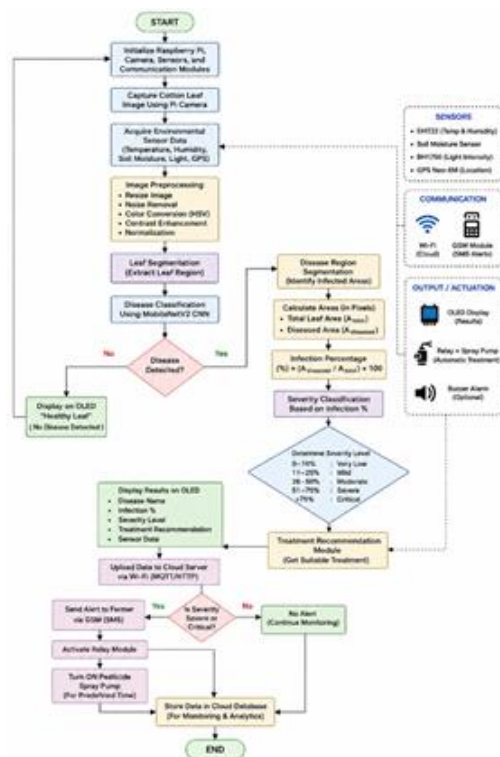
The deep learning model analyses the leaf image and determines whether the leaf is healthy or infected. If no disease is detected, the system displays a healthy leaf status and continues monitoring. If a disease is identified, the system proceeds to disease region segmentation, where infected portions of the leaf are isolated and highlighted.

Next, the system calculates the infection percentage by measuring the diseased area and comparing it with the total leaf area. The percentage of infected pixels is computed to determine the extent of disease spread on the leaf surface. Based on the calculated infection percentage, the system classifies disease severity into predefined categories such as Very Low, Mild, Moderate, Severe, or Critical.

Once the severity level is determined, the treatment recommendation module generates suitable control measures according to the detected disease type and infection level. Appropriate fungicides, pesticides, or preventive actions are suggested to assist farmers in managing the disease effectively. The generated results, including disease name, confidence score, infection percentage, severity level, treatment recommendation, and environmental sensor values, are displayed on the OLED screen and simultaneously uploaded to a cloud server through Wi-Fi using MQTT or HTTP protocols. This enables real-time remote monitoring through a web or mobile dashboard.

The system continuously evaluates the severity level. If the severity reaches a predefined threshold such as Severe or Critical, an SMS alert is sent to the farmer

through the GSM module. Additionally, the relay module can automatically activate a pesticide spray pump to perform treatment in the affected area. Finally, all disease information, sensor readings, treatment records, and alert logs are stored in a cloud database for future analysis and monitoring. The system then returns to the monitoring state and repeats the process for newly captured cotton leaf images, thereby providing continuous and intelligent crop disease management.



IV. HARDWARE ARCHITECTURE

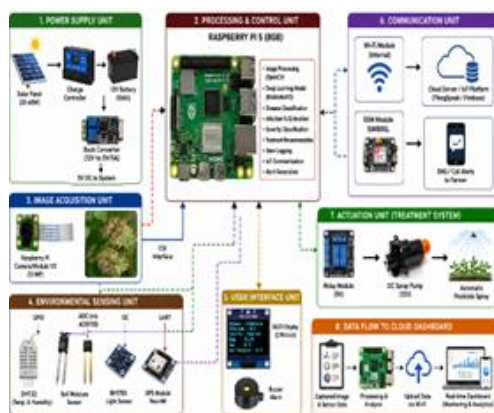


Figure 2. Complete Hardware Architecture

The proposed IoT-Based Automatic Cotton Leaf Disease Detection, Infection Severity Estimation, and Treatment Recommendation System operates by integrating image processing, deep learning, environmental sensing, wireless communication, and automated actuation technologies into a single Raspberry Pi-based platform. The hardware architecture continuously monitors cotton plants, detects diseases at an early stage, estimates infection severity, and provides appropriate treatment recommendations while enabling remote monitoring through cloud connectivity. The overall operation begins with image acquisition and environmental data collection, followed by disease identification, severity assessment, recommendation generation, cloud communication, and automated response actions.

2. System Initialization

When power is supplied through a battery, solar panel, or AC adapter, the Raspberry Pi 5 initializes all connected hardware modules.

3. Cotton Leaf Image Acquisition

The Raspberry Pi Camera Module captures high-resolution images of cotton leaves at predefined time intervals or on demand. The camera is mounted at a suitable height above the crop canopy to ensure clear visibility of leaf surfaces. Images are captured under natural lighting conditions and immediately transferred to the Raspberry Pi through the Camera Serial Interface connection.

4. Environmental Data Collection

Simultaneously, environmental sensors DHT22 Sensor, Soil Moisture Sensor and BH1750 Sensor continuously monitor field conditions that influence disease development.

5. Image Pre-processing

The captured leaf image may contain noise, shadows, or lighting variations. Therefore, image pre-processing with Improve image quality, Enhance disease visibility and Increase classification accuracy is performed before disease analysis.

6. Leaf Segmentation

After pre-processing, the system separates the leaf from the background using image segmentation techniques. Leaf segmentation isolates only the leaf region while removing unwanted objects such as Focus analysis on leaf area, Reduce computational complexity and Improve disease localization.

7. Disease Detection and Classification

The segmented leaf image is passed to the MobileNetV2 deep learning model stored on the Raspberry Pi. The CNN model analyses visual disease symptoms such as Leaf diseases such Healthy, aphids, armyworm infestation, bacterial blight, powdery mildew and target spot.

8. Disease Area Extraction

If a disease is detected the infected regions are isolated using image segmentation algorithms using Identify affected region, Measure disease spread and Support severity estimation. The diseased portion is highlighted and separated from healthy tissue.

9. Infection Percentage Estimation

Instead of only classifying disease, calculate infected area.

- Step 1: Segment leaf area.
- Step 2: Segment diseased region.
- Step 3: Calculate infected pixels.

Infection Percentage=Diseased Area/Total Leaf Area
X 100

Performance Evaluation

Disease Classification Metrics with have Accuracy, Precision, Recall, F1-score and Confusion Matrix.

- TP (True Positive): The actual value is positive, and the model correctly predicted it as positive.
- TN (True Negative): The actual value is negative, and the model correctly predicted it as negative.
- FP (False Positive): The actual value is negative, but the model incorrectly predicted it as positive.
- FN (False Negative): The actual value is positive, but the model incorrectly predicted it as negative.

$$\text{Accuracy}=(\text{TP}+\text{TN})/(\text{TP}+\text{TN}+\text{FP}+\text{FN})$$

9. Date set of Cotton Leaf

Random Dataset Images

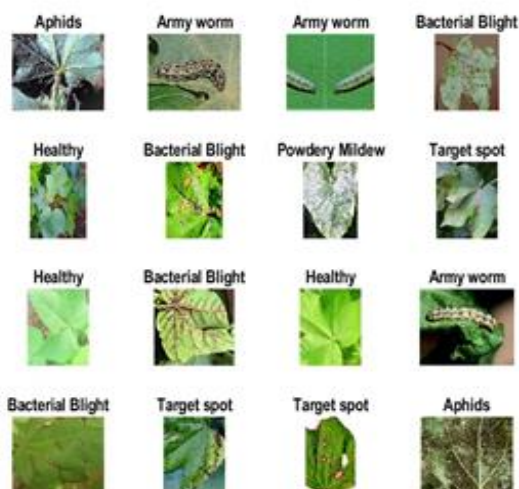


Figure 3. Cotton Leaf

From 3000 data set it's randomly selected dataset Images which is used for identification of Diseases according to 6 various class of diseases and randomly process for identification of infection on leaf and provide suggestion of treatment according to percentage of infection on it.

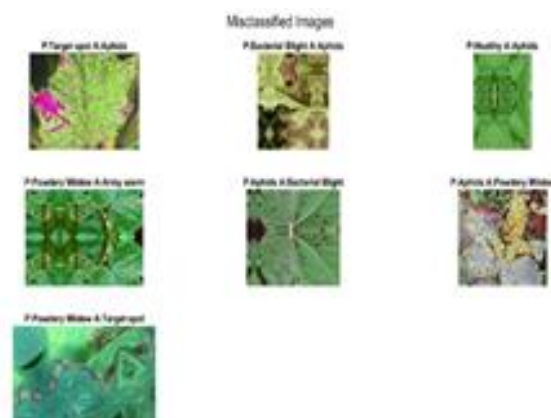


Figure 4. Misclassified Image

V. RESULT



Figure 5. Healthy Leaf Imag

Infection Area = 65.23 %

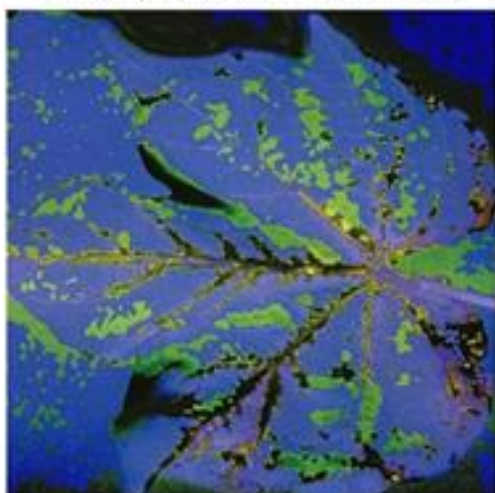


Figure 6. Bacterial Blight Leaf

Infection Area = 67.38 %

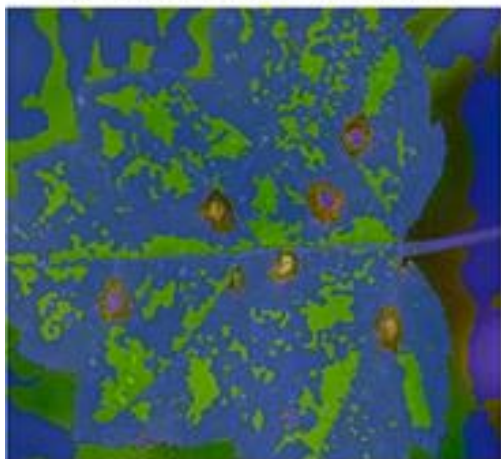


Figure 7.Target Spot Leaf

Infection Area = 59.61 %

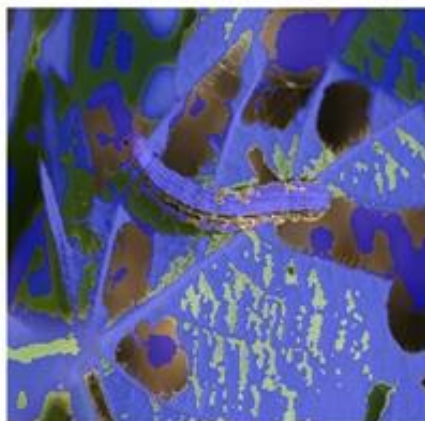


Figure 8. Army worm Leaf

Infection Area = 56.70 %



Figure 9. Powdery Mildew Leaf

1. Confusion Matrix Analysis

		Confusion Matrix (Accuracy = 97.7778%)					
True Class	Aphids	60					
	Army worm		58	1			1
	Bacterial Blight	2		57			1
	Healthy				60		
	Powdery Mildew			1		59	
	Target spot				2		58
		Predicted Class					
		Aphids	Army worm	Bacterial Blight	Healthy	Powdery Mildew	Target spot

Figure 10. Confusion Matrix Analysis

The confusion matrix indicated that most disease classes were accurately recognized. Minor misclassifications occurred between Alter aria and Cercospora diseases because of similar lesion patterns on infected leaves.

1. Performance Metrics

Table 1. Performance Metric

<i>Metric</i>	<i>Value (%)</i>
Accuracy	98.89 %
Precision	93.81 %
Recall	94.12 %
F1-Score	93.96 %

2. Severity Classification

Based on the infection percentage, disease severity is automatically categorized.

Table 2. Severity Level

<i>Infection Percentage</i>	<i>Severity Level</i>
0 – 10 %	Very Low
11 – 25 %	Mild
26 – 50 %	Moderate
51 – 75 %	Severe
>75 %	Critical

The experimental results confirm that the proposed Raspberry Pi-based smart agriculture system effectively performs automatic cotton leaf disease diagnosis and infection severity estimation. The model achieved high classification accuracy while maintaining low computational complexity suitable for edge deployment. The infection estimation module accurately quantified diseased regions, enabling reliable severity assessment. Integration of environmental sensors and IoT communication enhanced crop monitoring capabilities, while the treatment recommendation and alert mechanisms supported timely disease management decisions. These findings indicate that the proposed solution can contribute significantly to precision agriculture by reducing crop losses, minimizing unnecessary pesticide application, and improving cotton yield through early disease detection and intelligent decision support.

VI. CONCLUSION

This study presents the design and implementation of an IoT-based automatic cotton leaf disease detection, infection severity estimation, and treatment recommendation system using Raspberry Pi for smart agriculture. The main goal is to create a low-cost, intelligent, and real-time solution that identifies cotton leaf diseases, estimates infection severity, monitors environmental conditions, and suggests suitable treatments to farmers.

Author Contributions

1. **Deepak R. Khadse:** Proposed the research idea, reviewed related work, designed the system, built the Raspberry Pi setup, integrated the sensors and camera, and managed the project.
2. **Dr. Pankaj H. Zope:** Guided the research, checked the results, reviewed the methods and findings, edited the paper, provided technical support, and approved the final manuscript.

Disclosure Statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

ORCID

If the authors have ORCID identification, it must be given in this section.

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