

Plant Disease Detector Usng ESP8266

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ABSTRACT

The Plant Disease Detector using ESP8266 will be an IoT-based system designed to identify plant diseases at an early stage by analysing leaf images. Plant diseases can significantly reduce crop production, and traditional detection methods are often slow, manual, and require expert knowledge. To overcome these limitations, this project will combine image processing, machine learning, and wireless communication to provide a fast and automated solution for plant health monitoring. In this system, a camera module will capture real-time images of plant leaves. These images will then be processed using techniques such as color analysis, texture extraction, and pattern recognition to detect visible symptoms of diseases. A trained Convolutional Neural Network (CNN), a common machine learning model for image processing, will classify each leaf as healthy or diseased. The ESP8266 microcontroller will play a key role by enabling Wi-Fi connectivity, which will allow the processed results to be sent to a cloud platform or a mobile application for remote monitoring.

Keywords:- ESP8266, IOT, CNN, CC, CV, SDA, SCL.

1. INTRODUCTION

The timely detection of plant diseases remains a significant challenge in agriculture, primarily due to the subtle and easily overlooked nature of early symptoms. Conventional reliance on manual inspection typically limited to once or twice daily fails to capture the continuous emergence and spread of pathogens. Initial signs such as minor leaf discoloration, slight moisture imbalances, or minute fungal spots are frequently missed. A delay of even a few days in identification allows diseases to proliferate, compromising entire crop sections and leading to substantial yield loss and economic damage. This challenge is compounded by the common lack of specialized knowledge required for accurate diagnosis. Many plant ailments present visually similar symptoms, increasing the risk of misidentification. This can result in the application of incorrect treatments or excessive, potentially harmful chemicals. In large-scale operations, the sheer geographical scope renders thorough manual inspection impractical and inefficient. Furthermore, volatile environmental factors such as unexpected rainfall, humidity spikes, or heat stress can rapidly accelerate disease outbreaks, demanding swift and precise intervention.

Consequently, a critical gap exists in current agricultural practice: the absence of a continuous, automated monitoring system capable of delivering real-time alerts at the earliest stage of infection. Modern sensor technology and the Internet of Things (IoT) present a viable solution by enabling constant surveillance of environmental and plant health parameters with far greater speed and accuracy than human observation permits. Implementing such a system would provide farmers with immediate notifications of anomalies, enabling preventative action before a disease becomes severe.

This problem extends beyond disease management to encompass broader farm operations. Traditional practices also depend heavily on manual inspection and intuition for critical decisions regarding irrigation, fertilization, and pest management. While effective on a small scale, these methods become inefficient and error-prone when applied to larger farmlands. Key environmental factors like temperature, humidity, and soil moisture are vital for plant health, yet the lack of real-time data often leads to suboptimal yields, resource wastage, and delayed corrective actions.

The emergence of Smart Farming or Precision Agriculture addresses these interconnected challenges. This transformative approach integrates sensor networks, microcontrollers, and communication technologies to facilitate the continuous, automated monitoring of field conditions, delivering actionable data directly to the farmer. By reducing dependency on manual, enhancing accuracy, and enabling data-driven decision-making, Smart Farming represents a fundamental shift. The Internet of Things is central to this evolution, creating joined systems where devices autonomously collect, communicate, and analyze data to provide remote, actionable insights.

Therefore, there is an urgent and clear need for a smart, accurate, and real-time plant health and environmental monitoring solution. Such a system aims to minimize reliance on manual observation, enable proactive disease

detection and resource management, and support informed decisions to ensure crop vitality, optimize resource use, and enhance overall agricultural sustainability.

2. LITERATURE REVIEW

Automated detection of crop leaf diseases is crucial in agricultural research, facilitating large-scale field monitoring and early infection identification. "Disease" refers to any condition impairing plant health. Such systems significantly enhance crop quality and yield.

This literature review examines various techniques and methodologies used for crop leaf disease detection. The papers analyzed below represent key research in the field and serve as the foundation for this survey. By synthesizing insights from these studies, the review seeks to advance innovative developments of innovative and higher effective detection techniques.

[1] Leaf disease detection follows these steps: true color images convert to HSV color space for hue analysis, green pixels mask out as background, and segmentation extracts key regions. Texture features contrast, energy, homogeneity, correlation derive from Spatial Gray level Dependence Matrices via color co-occurrence analysis

[2] The detection process involves multiple steps. An initial true color image transforms into HSV color space a descriptor isolating the hue component for analysis. Green pixels receive zero/background values via masking, excluding irrelevant areas. This segmentation produces meaningful segments. Texture analysis applies color co-occurrence methods, computing Spatial Gray level Dependence Matrices parameters contrast, energy, local homogeneity, and correlation from hue content.

[3] The system comprises three stages: (i) Leaf segmentation, (ii) Disease segmentation, and (iii) Disease classification. Leaf segmentation uses LAB color space, followed by Self-Organizing Feature Map clustering and Back Propagation Neural Network color feature extraction. Disease segmentation employs a genetically optimized Self Organizing Feature Map for grape leaves, with Support Vector Machine classification. Gabor filters enhance leaf disease color feature analysis.

[4] Captured images undergo enhancement, followed by color segmentation using Sobel and Canny edge detection. The HPCCDD algorithm handles image classification and diseased spot identification. Farmers submit images directly a) post-identification b) optimal disease c) pest control solutions.

[5] This system regularizes and extracts eigenfeatures from cotton leaf images using scatter matrices derived from 100 samples. A within-class scatter matrix decomposes into disease-specific subspaces via pixel value variation analysis. Final feature extraction, dimensionality reduction, and disease identification occur through feature comparison.

[6] The RGB image converts to another color space, where K-means clustering identifies dominant green pixels. These pixels mask out via Otsu's thresholding. The segmented diseased image then transforms to HSI format for Color Co-occurrence Matrix texture feature extraction, followed by pre-trained neural network recognition.

[7] This methodology proposes early and accurate plant disease detection using diverse image processing techniques and an Artificial Neural Network (ANN). The process begins with capturing sample images. These RGB images are converted to the CIELAB color scale for segmentation. The images are then filtered using a Gabor filter to extract texture and color features, and finally, an ANN is employed for image recognition and classification.

[8] The image first converts from RGB to grayscale, then applies Low-Pass Filter (LPF) and Gaussian filtering. K-means clustering segments the image, followed by graph cut energy minimization. Color features extract from 64-block RGB partitioning (averaged pixel colors per block), RGB-to-YCbCr conversion, 8x8 DCT on Y/Cb/Cr components, and zigzag scanning for color layout descriptors. Shape features compute via area, perimeter, and sharpness parameters.

[9] Images are acquired using a digital camera and enhanced or smoothed with the image applies a Low-Pass Filter and Gaussian filter. An active contour model "snakes" segments the image, while seven Hu's moments invariant to rotation, scale, and translation extract as features for classifier training. Finally, this feature vector is used in a feed-forward back-propagation network for disease classification.

[10] This study compares the effects of converting RGB images to grayscale, YCbCr, HSI, and CIELAB color spaces during the preprocessing stage to detect diseased spots on leaves. The converted image is smoothed using a median filter to remove noise. Specific color planes across four methods:

Method 1: RGB to grayscale, with Otsu's thresholding applied directly.

Method 2: RGB to YCbCr, with Otsu's thresholding applied to the "Cr" plane after filtering.

Method 3: RGB to HSI, with Otsu's thresholding applied to the "H" component after filtering.

Method 4: RGB to CIELAB, with Otsu's thresholding applied to the "A" component after filtering. After comparing all methods, the CIELAB color model was selected as the most effective.

[11] Diseased rice leaf samples are photographed in macro mode with a digital camera. Images undergo preprocessing by enhancing brightness/contrast and converting to HIS color space for segmentation. Entropy-

based bi-level thresholding with 8-connectivity extracts diseased spots (300×300 to 1500×1500 pixels), followed by SOM neural network classification.

3. IMPLIMENTATION OF SYSTEM

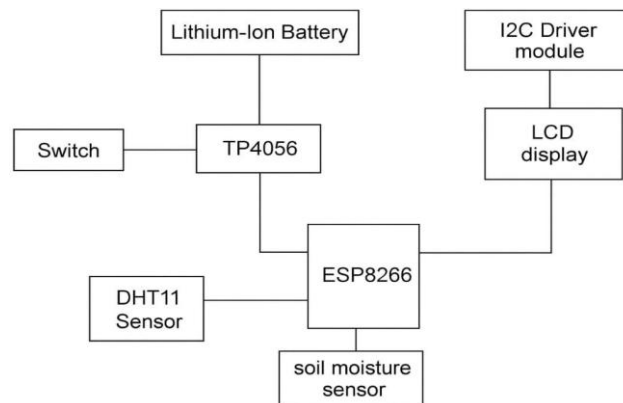
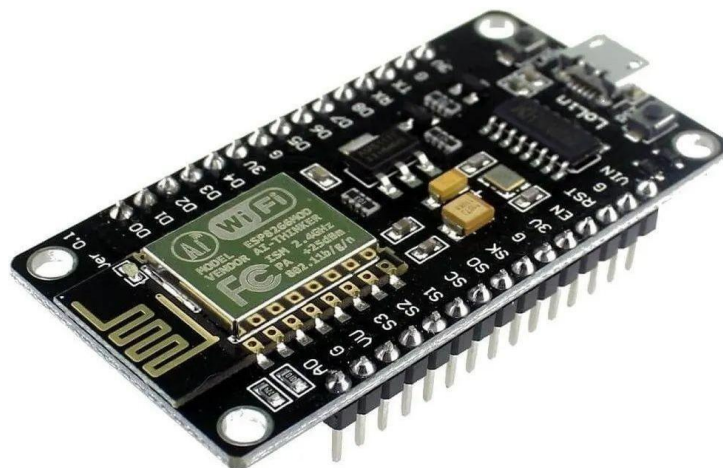


Fig.1 Block Diagram of Working of ESP8266 Complete.

ESP8266 IOT



Compact, low-cost Wi-Fi microcontroller (ESP8266/ESP-82) with 2.4 GHz Wi-Fi, 32-bit processor, GPIO/UART/SPI/I2C interfaces. Ideal for low-power IoT like plant monitoring and smart agriculture. Arduino-compatible with strong community support.



Fig.2 Complete Setup.

4. RESULTS

Performance evaluation of the IOT based Leaf infection detection system shows that the overall functionality is efficient, accurate, and reliable for real-world agricultural use. Each component was tested individually as well

as in the complete system, and the results confirm that the device performs consistently in different environmental conditions.

The soil moisture sensor responded very well during testing. When the soil was dry, the sensor values dropped immediately, triggering a “Low Moisture” alert on the mobile app. When water was added, the sensor value increased instantly, showing that the sensor is sensitive and reacts quickly to even small changes in moisture content.

The temperature and humidity sensor (DHT11/DHT22) also demonstrated stable and accurate performance. Throughout the day, the sensor successfully captured fluctuations in temperature and humidity. These values are crucial because conditions like high humidity can lead to fungal diseases. The sensor’s steady output proved that it can help monitor disease-related environmental changes effectively.

The ESP8266 microcontroller showed strong Wi-Fi connectivity. It transmitted sensor data to the mobile application without delay, ensuring real-time monitoring. Even during network fluctuations, the device reconnected automatically, proving its reliability. The mobile app received instant alerts whenever a parameter exceeded the safe threshold, which is essential for early disease detection.

The LCD display presented clear, readable information and updated values without lag or flicker. The power system, consisting of an 18650 battery, TP4056 charging module, and voltage booster, provided stable and long-lasting power, allowing the system to run continuously for several hours.

Overall, the performance analysis confirms that the system functions effectively in real-time plant health monitoring. It successfully detects abnormal conditions early, provides timely alerts, and helps prevent plant damage. The results prove that the IoT-based system is suitable for smart farming and can significantly support farmers in improving crop health

Tomato Disease Result

Heathly Leaf



Disease Leaf



5. CONCLUSION

IoT technology can be effectively used for early plant disease detection and real-time monitoring of crop health. By integrating an ESP8266 microcontroller with sensors soil moisture, temperature and humidity, leaf and light conditions. sensor, the system continuously observes critical environmental parameters that influence plant growth and disease development.

6. REFERENCES

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