# **Plant Disease Detection Using Drone And Machine Learning**

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#### Abstract

Identification of the plant diseases is the key to prevent the losses in the yield and quantity of the agricultural product. The studies of the plant diseases mean the studies of visually observable patterns seen on the plant. Health monitoring and disease detection on plant is very critical for sustainable agriculture. Currently, drones, play a pivotal role in the monitoring of plant pathogen spread, detection, and diagnosis to ensure crops health status. Drones have many potential uses in agriculture, including reducing manual labor and increasing productivity. Drones may be able to provide early warning of plant diseases, allowing farmers to prevent costly crop failures. This project presents a smart plant disease detection system using drones and machine learning. A drone equipped with a camera captures images of crops, which are analyzed using a Python-based machine learning model to detect signs of disease. The NodeMCU microcontroller, integrated with a GPS module, tracks the drone's location, while a Wi-Fi module enables real-time data transmission. Embedded C is used for microcontroller programming, enabling seamless integration between hardware and software for efficient, real-time plant health monitoring.

**Keywords:** Raspberry Pi Pico, LCD Display, WIFI module, Node MCU Esp 8266, GPS Module Neo-6M, E88 Pro Drone, Embedded C, Python.

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#### I. Introduction

India is a cultivated country and about 70% of the Population depends on agriculture[1].Farmers have large range of diversity for selecting various suitable crops and finding the suitable pesticides for plant[2].Hence, damage to the crops would lead to huge loss in productivity and would ultimately affect the economy. By leveraging a drone's ability to rapidly capture high-resolution aerial images across extensive agricultural fields, the system seeks to monitor crop health in real-time[3].Drones offer a flexible and efficient platform for large-scale field monitoring by capturing high-resolution aerial imagery of crops. These images can be analyzed using machine learning algorithms to identify disease symptoms at early stages with high accuracy[4]. This integration of drone-based imaging and intelligent analysis not only enhances precision agriculture practices but also enables proactive decision-making for disease management. Ultimately, this initiative is designed to reduce crop losses, lower inspection costs, and support sustainable farming practices by providing farmers with a proactive tool for crop management[5]. A plant disease detection system using a Raspberry Pi integrated with a drone. The drone is equipped with a camera and flies over the fields to capture real-time images of crops. These images are then processed by the Raspberry Pi using machine learning to detect symptoms of plant diseases. This is a difficult objective because a lot of the agricultural industry depends on uncontrollable factors, such the weather, the quality and quantity of irrigation water, and the state of the soil. Therefore, in order to maximize resource utilization and raise agricultural productivity, precision technologies like drones must be adopted[6]. In precision agriculture, drones have been applied in a variety of ways, and new applications are always being investigated. Drone applications include the identification of plant diseases, which have been the subject of much research. Early disease identification and stopping the spread of infection to reduce crop loss are two advantages of deploying drones[7]. The aim of this project is to design and implement a plant disease detection system that utilizes dronecaptured images and machine learning algorithms to accurately identify and classify crop diseases in real-time.

# **II.Research Method**

This research adopts a combination of experimental and observational design, utilizing drone-based remote sensing in conjunction with supervised machine learning techniques to detect and classify plant diseases. The methodology is structured into several phases, including data collection, image preprocessing, feature extraction, model development, and evaluation. Data collection begins with the deployment of drones equipped with high-resolution RGB and/or multispectral cameras to capture aerial images of crop fields. Specific crops prone to diseases—such as tomato, wheat, or rice—are targeted to ensure the relevance and applicability of the dataset. Field surveys are conducted in selected agricultural zones to gather a diverse set of images under varying environmental conditions. To support supervised learning, ground truth labelling is carried out by agronomists or experts, who manually inspect and annotate a subset of the collected images to ensure accurate classification. Following data acquisition, image preprocessing techniques are applied to enhance image quality and prepare the data for analysis. This includes the removal of background noise using image filters and the application of segmentation methods-such as K-means clustering or thresholding-to isolate plant regions from non-relevant backgrounds. Additionally, data augmentation strategies, including rotation, scaling, and flipping, are employed to artificially expand the dataset and improve model generalization while reducing the risk of overfitting. Next, feature extraction is conducted to identify meaningful patterns that signify the presence of disease. Colour features are analyzed to detect symptoms such as vellowing or brown spots, while texture features are extracted using techniques like the Gray-Level Cooccurrence Matrix (GLCM) to quantify irregularities in leaf surfaces. Shape and edge detection algorithms are also utilized to identify lesions, deformations, or abnormal growth patterns. For model development, various machine learning algorithms are employed, with a focus on Convolutional Neural Networks (CNNs) due to their effectiveness in image classification tasks. Alternatives such as Support Vector Machines (SVM) and Random Forests may also be tested for comparative purposes. The dataset is typically divided into training and testing sets, commonly in an 80:20 ratio, to ensure robust validation. Model performance is assessed using metrics such as accuracy, precision, recall, F1-score, and a confusion matrix. The implementation of this methodology requires specific tools and technologies. On the hardware side, drones equipped with GPS and high-resolution imaging capabilities are essential. On the software side, programming environments and libraries such as Python, TensorFlow/Keras, OpenCV, OGIS, and Scikit-learn are employed for data handling, model development, and geo-referencing. Finally, ethical and practical considerations are taken into account throughout the research process

#### **Problem Identification**

Agricultural productivity is critically dependent on the early and accurate detection of plant diseases. Traditionally, disease identification is performed manually by farmers or agricultural experts through visual inspection, which is time-consuming, labor-intensive, and often subjective. This method is particularly ineffective for large-scale farms where consistent and timely monitoring of every plant is impractical. Additionally, the delay in detecting diseases often leads to widespread crop damage, resulting in significant economic losses and reduced food security.

#### System Design

The proposed system integrates **drone technology** with **machine learning algorithms** to detect plant diseases efficiently and accurately. The design follows a modular approach, consisting of several key components working together in a pipeline to capture, process, analyze, and report plant health data. **Table.1. Conventional Neural Network architecture used for image classification** 

Layer (type)	Output shape	Param #
conv2d_1 (conv2Dc)	(None, 222, 222, 32)	896
max_pooling2d (MaxPoolind2D)	(None, 111, 111, 32)	0
conv2d_2 (Conv2D)	(None, 109, 109, 64)	18,496
max_pooling2d_1 (Maxpooling2D)	(None, 54, 54, 64)	0
conv2d_3 (Conv2D)	(None, 52, 52, 128)	73, 856
max_pooling2d_2 (Maxpooling2D)	(None, 26, 26, 128)	0
flatten (Flatten)	(None, 86528)	0
dense (Dense)	(None, 512)	44, 302, 848
dropout (Dropout)	(None, 512)	0
dense_1 (Dense)	(None, 10)	5,130

#### Dataset

Early Blight: The fungus Alternaria solani is the source of early blight, which causes dark lesions to form on the bottom leaves of tomato plants. These lesions, which often have rings around them, can spread to the fruit and stems, causing the plant to become defoliated and producing less.



Fig.1. Early Blight

Bacterial Spot: On leaves, stems, and fruit, this bacterial disease which is brought on by Xanthomonas campestris PV. Vesicatoria appear as tiny, dark lesions with yellow haloes. Bacterial spot can cause yield loss, defoliation, and a decrease in fruit quality. Bacterial Leaf Streak: Narrow, translucent streaks appear between the veins of the leaf. These streaks are usually yellowish or brown and run parallel to the leaf veins. Brown Spot: It infects leaves, stems, and grains, leading to brown, circular to oval lesions. Blast: Blast disease is primarily caused by the fungus Magnaporthe oryzae, which infects several cereal crops, particularly rice. The pathogen thrives in warm, humid environments and is disseminated through airborne spores.



# **III.Proposed Topology**

Fig:2. Circuit Diagram

#### Training Phase:

Data Acquisition from standard Repositories through drones: Obtain a wide range of crop image datasets from common libraries that include tagged examples of both healthy and diseased crops. Make use of drones that have high-resolution cameras to take pictures of crops in fields to assure all types and phases of growth are covered. For supervised learning, assure that pictures are appropriately labeled with the appropriate disease types. Pre-processing: To normalize obtained images for training, apply pre-processing. Images should be resized to a standard resolution that can be fed into CNN. A similar scale, such as [0, 1], should be applied to pixel values to promote convergence during training. Use data augmentation methods to enhance the diversity and resilience of your datasets, such as scaling, flipping, and rotation. CNN Architecture Design: Network's depth (the number of layers). sizes and strides of convolutional filters. pooling techniques (such as maximum pooling). Training the CNN Classifier Training. Divide the pre- processed dataset into training and validation sets using a ratio of, say, 80/20 or 70/30.

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Testing Phase:

Testing Data Acquisition: Make sure a distinct testing dataset includes a variety of crop types, disease severity, and environmental circumstances by gathering information from various agricultural areas. Utilize drones to take consistent, high-quality photos of crops in the testing zones while ensuring picture resolution. Pre-processing for Testing: Resize, normalize, and enhance the holdout dataset using the same pre- processing techniques as the training dataset. Evaluation of CNN Classification: To evaluate overall performance, calculate the F1 score, recall, precision, and accuracy of classification. Create ROC curves and confusion matrices to examine model behavior across various disease classes. Determine whether the outturn of the classification have any biases or flaws. Disease Identification and Remedial Measures: Predict crop disease labels in the testing dataset by applying the learned CNN classifier. Using the database of recognized diseases and their characteristics, retrieve the appropriate disease names and recommend corrective actions. Verify the efficacy of recommended actions by consulting with experts or conducting field tests. Iterative Improvement: Refine the CNN design, training regimen, and database contents by taking into account input from test outcomes. Iterate the approach to resolve any shortcomings or difficulties found, guaranteeing ongoing progress in the precision of disease diagnosis and remediation suggestions.

# **IV.Hardware Results**

The implemented system successfully retrieves and displays real-time GPS coordinates using the GPS module interfaced with the Arduino board. The latitude and longitude values are shown clearly on the IOT log data using laptop allowing real-time tracking of location data. The setup also includes an ESP8266 module, which can be used for wireless transmission of the data if needed.During testing, the device consistently displayed accurate location coordinates, confirming the correct integration and functionality of the hardware components. This system can be effectively used in applications like smart agriculture and remote environmental monitoring.. By examining leaf photos, our algorithm is able to identify night different forms of leaf diseases: Bacterial Blight, Bacterial Leaf Streak, Blast, Brown Spot, Fake Smut, Discoloration, Sheat Blight, Sheat Rot, Healthy. By default, a healthy leaf is displayed. With the accurate disease identification this technology provides, crop management interventions can be made on time.

# V.Prototype

In this prototype, a drone equipped with a camera captures real-time images of crops, which are then processed using a machine learning model trained to detect plant diseases. The disease detection results are paired with GPS location data obtained from a GPS module connected to an Arduino board. The system uses an ESP8266 Wi-Fi module to enable wireless transmission of data, while a 16x2 LCD screen displays the detected disease status along with the corresponding GPS coordinates. This integration allows for precise identification and mapping of affected areas in a farm, providing a foundation for targeted agricultural interventions and efficient disease management.



Fig:3. Hardware Prototype



# Fig.4. Output for Blast

# Fig.5. Analysis of Plant Disease using Drone

The proposed system was tested on aerial images of crop fields collected using drones equipped with high-resolution RGB cameras. A dataset comprising both healthy and diseased plant images was prepared and annotated with expert input. The machine learning pipeline, using a Convolutional Neural Network (CNN), was trained to classify the plant health status based on visual features extracted from the preprocessed drone imagery.

The integration of drones and machine learning provides a viable, modern solution for real-time plant disease monitoring in agriculture. The system improves decision-making for farmers by offering early detection, spatial mapping, and scalable monitoring. The high accuracy and precision of the CNN model demonstrate the potential of AI in precision agriculture. To further enhance this system, future work may include expanding the dataset to cover more crop types and diseases, improving real-time processing capability through edge AI hardware, and integrating weather data to contextualize disease outbreaks.

#### VI.Conclusion

The project successfully demonstrates an efficient and automated method for detecting plant diseases using drone-captured imagery and machine learning techniques. By integrating drone technology for real-time image acquisition and applying a Convolutional Neural Network (CNN) model for analysis, the system can accurately identify various plant diseases . This approach not only reduces the need for manual monitoring but also enables early detection, helping farmers take timely actions to prevent crop loss. Overall, the proposed system offers a scalable and cost-effective solution for smart agriculture, promoting increased productivity and sustainable farming practice

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