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PlantDiseaseDetectionUsingDroneAndMachineLearning

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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 diseasesmean the studies of visually observable patterns seen on the plant. Health monitoringanddiseasedetectiononplantisverycriticalforsustainableagriculture.Currently,drones,playapivotal rolein the monitoringof plant pathogen spread,detection,and diagnosisto ensurecropshealth status. Droneshave manypotentialusesinagriculture,includingreducingmanuallaborandincreasingproductivity.Dronesmaybeable 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 NodeMCUmicrocontroller,integratedwithaGPSmodule,tracksthedrone'slocation,whileaWi-Fimoduleenables 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 tothecropswouldleadtohugelossinproductivityandwouldultimatelyaffecttheeconomy. Byleveragingadrone's abilitytorapidlycapturehigh-resolutionaerialimagesacrossextensiveagriculturalfields,thesystemseekstomonitor crophealthinreal-time[3].Dronesoffera flexibleandefficientplatformfor large-scalefieldmonitoringbycapturing high-resolution aerialimageryofcrops. Theseimages can beanalyzed usingmachinelearningalgorithms toidentify 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 detectionsystemusingaRaspberryPiintegratedwithadrone.Thedroneisequippedwithacameraandfliesoverthe 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 qualityand quantityof 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 applicationsarealwaysbeinginvestigated.Droneapplicationsincludetheidentificationofplantdiseases,whichhave beenthesubjectofmuchresearch.Earlydiseaseidentificationandstoppingthespreadofinfection toreducecroploss aretwoadvantagesofdeployingdrones[7].Theaimofthisprojectistodesignandimplementaplantdiseasedetection system that utilizes drone-captured images and machine learning algorithms to accurately identify and classify crop diseases in real-time.

II. ResearchMethod

This research adopts a combination of experimental and observational design, utilizing drone-based remotesensingin conjunction with supervisedmachinelearningtechniquestodetect and classifyplantdiseases. The methodology is structured into several phases, including data collection, image preprocessing, feature extraction, model development, and evaluation. Data collection begins with the deployment ofdrones 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 therelevance and applicability of the dataset.Fieldsurveysareconductedinselectedagriculturalzonestogatheradiversesetofimagesundervarying environmentalconditions.Tosupportsupervisedlearning,groundtruth labellingiscarriedoutbyagronomistsor experts, who manually inspect and annotate a subset of the collected images to ensure accurate classification. Followingdataacquisition,imagepreprocessingtechniquesareappliedtoenhanceimagequalityandpreparethe data for analysis. This includes the removal of background noise using image filters and the application of segmentation methods—such asK-meansclustering or thresholding—toisolateplantregionsfromnon-relevant backgrounds. Additionally, data augmentation strategies, includingrotation, scaling, andflipping, areemployed to artificiallyexpand the dataset and improve model generalization while reducing therisk of overfitting. Next, featureextractionisconductedtoidentifymeaningfulpatternsthatsignifythepresenceofdisease.Colourfeatures are analyzed to detect symptoms such as yellowing or brown spots, while texture features are extracted using techniques like the Gray-Level Co-occurrence Matrix (GLCM) toquantifyirregularities in leaf surfaces. Shape andedgedetectionalgorithmsarealsoutilizedtoidentifylesions,deformations,orabnormalgrowthpatterns.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 dividedintotrainingandtestingsets,commonlyinan80:20ratio,toensurerobustvalidation.Modelperformance 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, QGIS, and Scikit-learn are employed fordatahandling,modeldevelopment,andgeo-referencing.Finally,ethicalandpracticalconsiderationsaretaken into account throughout the research process

ProblemIdentification

Agricultural productivity is critically dependent on the early and accurate detection of plant diseases. Traditionally,diseaseidentificationisperformedmanuallybyfarmersoragriculturalexpertsthroughvisualinspection, which istime-consuming, labor-intensive, andoften subjective. Thismethodisparticularlyineffective for large-scale farms where consistent and timely monitoringof every plant isimpractical. Additionally, the delayindetecting diseases oftenleadstowidespreadcropdamage,resultinginsignificanteconomiclossesandreducedfoodsecurity.

SystemDesign

Theproposedsystemintegrates**dronetechnology**with **machinelearningalgorithms**todetectplant diseases efficientlyand 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.ConventionalNeuralNetworkarchitectureusedforimageclassification

Layer(type)	Outputshape	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 leavesoftomatoplants.Theselesions,which often haveringsaroundthem, can spreadtothefruitandstems, causing the plant to become defoliated and producing less.

Fig.1. EarlyBlight

Bacterial Spot: On leaves, stems, and fruit, this bacterial disease which is brought on byXanthomonas campestris PV. Vesicatoria appear astiny, darklesions with yellowhaloes. Bacterial spot can cause yield loss, defoliation,and a decreasein fruit quality. Bacterial Leaf Streak: Narrow, translucent streaks appear between theveins of the leaf. Thesestreaksareusuallyyellowish or brown andrunparallel totheleafveins.Brown Spot:Itinfectsleaves, stems, and grains, leading to brown, circular to oval lesions. Blast: Blast disease is primarilycaused bythe fungus Magnaporthe oryzae, which infects several cereal crops, particularlyrice. The pathogen thrives in warm, humid environments and is disseminated through airborne spores.

III. ProposedTopology

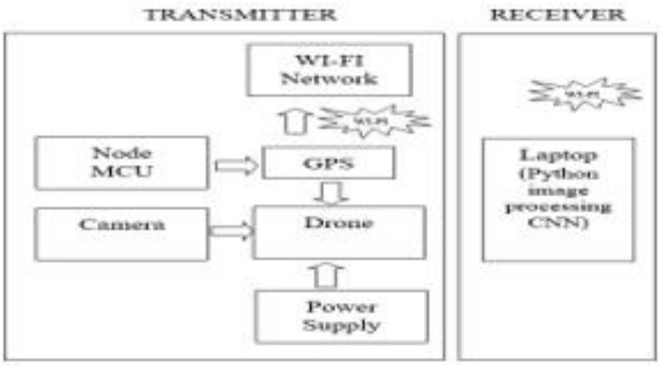


Fig:2.Circuit Diagram

TrainingPhase:

Data Acquisition from standard Repositories through drones: Obtain a wide range of crop image datasets from commonlibrariesthatincludetaggedexamplesofbothhealthyanddiseasedcrops.Makeuseofdronesthathavehigh-resolution cameras to take pictures of crops in fields to assure all types and phases of growth are covered. For supervised learning,assurethat picturesareappropriatelylabeled with theappropriatediseasetypes. Pre-processing: To normalize obtained images for training, apply pre-processing. Images should be resized to a standard resolution that can be fed intoCNN. 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,androtation.CNNArchitectureDesign:Network'sdepth(thenumberoflayers).sizesandstridesof convolutional filters.poolingtechniques (such as maximumpooling).TrainingtheCNN Classifier Training.Divide thepre-processed datasetintotrainingandvalidation setsusingaratioof, say, 80/20or 70/30.Usethetrainingsetto train theCNNmodel, andthen usebackpropagation and gradient descent tooptimizethehyperparameters. Database CreationcontainingFeaturesoftheDisease:Createadatabasewithcharacteristicsofrecognizedagriculturaldiseases, such as environmental variables, spatial patterns, and visual symptoms

TestingPhase:

Testing Data Acquisition: Make sure a distinct testingdataset includes a varietyof 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,andenhancetheholdoutdatasetusingthesamepre-processingtechniquesasthetraining dataset.Evaluation ofCNNClassification:Toevaluate overall performance, calculatetheF1 score,recall, precision, andaccuracyofclassification.CreateROC curvesandconfusion matricestoexaminemodel behavior acrossvarious 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 recommendcorrectiveactions. Verifytheefficacyofrecommendedactions byconsulting with expertsor conducting field tests. Iterative Improvement: Refine the CNN design, training regimen, and database contents by taking into accountinputfromtestoutcomes.Iteratetheapproachtoresolveanyshortcomingsor difficultiesfound,guaranteeing ongoing progress in the precision of disease diagnosis and remediation suggestions.

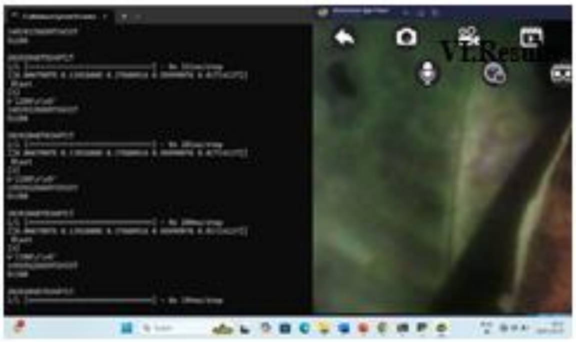
IV. HardwareResults

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,ouralgorithmisabletoidentifynightdifferentformsofleafdiseases:BacterialBlight, BacterialLeafStreak, Blast,BrownSpot,FakeSmut,Discoloration,SheatBlight,SheatRot,Healthy.Bydefault,ahealthyleafisdisplayed. With the accurate disease identification this technology provides, crop management interventions can be made on time.

V. Prototype

Inthisprototype, adroneequippedwitha cameracapturesreal-timeimagesofcrops, whicharethenprocessedusing a machinelearningmodel trained to detect plant diseases. The diseasedetection resultsare paired with GPSlocation 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 GPScoordinates. Thisintegration allows for precise identification andmapping of affected areasin a farm, providing a foundation for targeted agricultural interventions and efficient disease management.

Fig:3. Hardware Prototype



VI.Results AndDiscussion

Fig.4.OutputforBlast

Fig.5.AnalysisofPlantDiseaseusing 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. Themachinelearning pipeline,using a Convolutional Neural Network (CNN), was trainedtoclassifytheplanthealthstatusbasedonvisualfeaturesextractedfromthepreprocesseddroneimagery.

The integration of drones and machine learning provides a viable, modern solution for real-time plant diseasemonitoringinagriculture.Thesystem improvesdecision-makingfor farmersbyofferingearlydetection, 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 mayinclude 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.

VII.Conclusion

Theproject successfullydemonstratesan efficientandautomatedmethod for detectingplantdiseasesusingdrone-captured imagery and machine learning techniques. By integrating drone technology for real-time image acquisition and applyinga Convolutional Neural Network (CNN) model for analysis, the system can accurately identifyvarious plant diseases . This approach not onlyreduces theneed for manual monitoring but also enables earlydetection, helping farmers take timelyactions 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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