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AI-Based Drone for Crop Disease Detection in Precision Agriculture

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Abstract - This research investigates the use of drones with artificial intelligence (AI) to identify crop diseases in precision agriculture. The suggested approach gives farmers precise and timely tools for regulating crop health by combining machine learning algorithms, remote sensing technology, and real-time monitoring. This method seeks to maximize harvest yields and minimize production losses by detecting diseases early on through the use of comprehensive disease databases and high-resolution imaging. This strategy is important because it can help with issues like food safety, agricultural production, and revenue loss—all of which are major concerns in poor countries. For big farms, traditional techniques of visual inspection by specialists are impractical due to their high cost and time requirements. Thus, using AI-powered drones to automate disease detection presents a workable way to improve agricultural sustainability and guarantee world food security.

1. INTRODUCTION

The rapid spread of pathogens makes it difficult for agriculture to preserve crop health. In order to maintain food security and avoid yield loss, early detection is essential. Conventional techniques are not as timely or efficient. With their sophisticated technologies, drones provide a promising way to quickly and accurately diagnose agricultural diseases. To feed the growing global population, agricultural food production must rise by at least 70% on a global scale.

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.

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. The scope of earlier review studies on drone applications in precision agriculture is constrained

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2. LITERATURE SURVEY

1. The paper by Elakkiya and Bhuvaneswari (2020) explores the use of drone technology in agriculture crop disease detection. Augmenting challenges in crop management due to various diseases, early detection and intervention can be given a paramount importance in minimizing crop losses. The authors propose the use of drones equipped with high- resolution cameras and sensors to capture images of crops and analyze them for disease symptoms[1].
2. The article "Review of Challenges and Opportunities in Implementing AI Technologies for Sustainable Agriculture" by Dong et al. (2021) discusses the various obstacles and potential advantages integrated with the application of artificial intelligence (AI) in sustainable agriculture. The authors highlight the benefits of AI technologies, such as increased efficiency, precision, and productivity in farming practices[2].
3. Mishra et al. (2020) propose a low-cost AI framework for crop disease detection using drones. The researchers highlight the importance of early detection of disease in crop management to ensure food security. They design an integrated system that combines drone technology, computer vision algorithms, and AI techniques to identify crop diseases accurately and in a timely manner. By utilizing drones, this framework offers a cost-effective solution for monitoring large agricultural areas[3].
4. The paper by Raza et al. (2019) directs attention to the application of deep learning algorithms for crop disease detection and diagnosis. It explores the ability to employ convolutional neural networks (CNNs) to classify and identify diseases in crop plants based on images. The authors highlight the advantages of deep learning techniques over traditional methods, such as higher authentic and processing times. They also discuss various CNN architectures and highlight their performance in crop disease detection[4].
5. In 2018, Liakos, K., et al. carried out a thorough analysis on the use of machine learning methods in agriculture. The study examined a number of agricultural topics, such as soil analysis, disease diagnosis, weed identification, and crop production prediction. The authors outlined the possible advantages of using machine learning to agriculture, including higher output, lower expenses, and better resource management[5].

6. The article "Intelligent Techniques for Agriculture Disease and Pest Management: Challenges and Perspectives" by Zhang et al. (2021) discusses the use of intelligent techniques in agriculture for disease and pest management. The authors highlight the challenges faced and provide perspectives on how intelligent techniques can address these issues[6].

3. PROPOSED METHOD

In this project we are proposed to develop UAV drones which would help the farmers to diagnose diseases of crops earlier. Machine learning based technology will assist farmers and agricultural agencies to scout areas of fields. Farmers can use either drone camera to monitor their fields in less time. This will also save the cost of labor associated with manual infield scouting. An early identification of diseases will also reduce pesticide application rates and cost. This application will increase the overall growth of crops and no need for identifying the diseases in long time. This application has user friendly interface. All communications between all the users is done through UAV drone, Display monitor and a remote controller. This technique is the cost-effective solution without expensive hardware or software requirement. The images acquired by UAV Drone will be processed on online server using Tensor flow, OpenCV and flask.

3.1 Dataset:

1. 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 becomedefoliated and producing less.

Figure 1. Early Blight

2. Late blight: Phytophthora infestans is the source of late blight, another fungal disease that damages fruit and leaves alike. If treatment is not received, it usually manifests as dark, water-soaked sores on the leaves that spread quickly and kill the plant.

3. 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.

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Figure 2. Bacterial Sp

4. Fusarium Wilt: Fusarium oxysporum f.sp. lycopersici is the fungus responsible for fusarium wilt, which causes yellowing and wilting of the lower leaves. Eventually, the entire plant may wilt and die due to vascular damage induced by the fungus.
5. Verticillium Wilt: Tomato plants wilt due to two fungus, Verticillium dahliae and Verticillium albo-atrum. Among the symptoms include yellowing and wilting of the leaves, which usually start on one part of the plant. Vascular discolouration may also be present.
6. Tomato Mosaic Virus: This virus causes mottling and mosaic patterns on tomato leaves, as well as distorted fruit and limited growth. It spreads through distorted plant matter, uncleaned instruments, and sap-sucking insects.
7. Tomato Yellow Leaf Curl Virus: This virus, which is spread by whiteflies, causes tomato leaves to become yellow, curl, and cup. It also causes slowed development and decreasedfruit yield.

3.2 Methodology

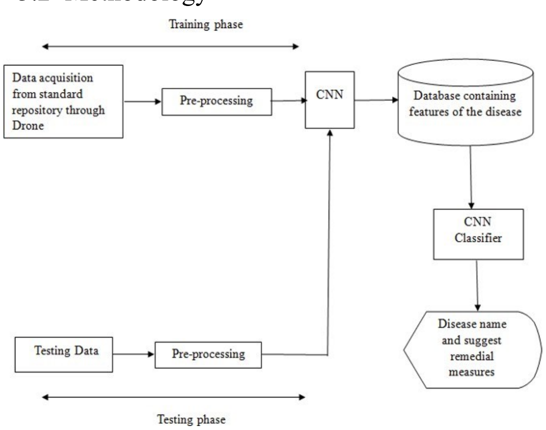

Figure 3. Methodology

Certainly, here's a detailed methodology including both training and testing phases for using AI- based drones for crop disease detection in precision agriculture:

Training Phase:

1. 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 takepictures 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.

2. 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.

3. CNN Architecture Design: Network's depth (the number of layers). sizes and strides of convolutional filters. pooling techniques (such as maximum pooling). Use strategies like dropout and

4. 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. Use the training set to train the CNN model, and then use backpropagation and gradient descent to optimize the hyperparameters. To speed up convergence and enhance generalization, use transfer learning by initializing the CNN with strength training on a sizable dataset (such as ImageNet). Utilizing validation data, track training progress and make necessary adjustments to learning rates or early stopping to avoid overfitting.

5. Database Creation containing Features of the Disease: Create a database with characteristics of recognized agricultural diseases, such as environmental variables, spatial patterns, and visual symptoms. Arrange the database such that it may be efficiently retrieved for classification, taking indexing and search methods into consideration. For a thorough analysis, provide metadata about the disease's severity, prevalence, and suggested corrective actions.

Testing Phase:

6. 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.

7. Pre-processing for Testing: Resize, normalize, and enhance the holdout dataset using the same pre-processing techniques as the training dataset.

8. 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.

9. 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.

10. 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.

4. PROPOSED SYSTEM

Neural network model that can classify images. There will be a website where this model is used.This model will be used by the website to detect plant leaf disease in real time.

1. High-resolution photos of crops in farming fields are taken by drones.
2. Standardize image sizes, normalize pixel values, and improve image quality.
3. To extract pertinent information from photos, use Convolutional Neural Networks (CNN).
4. Using attributes that are retrieved, train CNN to distinguish between photos of healthy and unhealthy crops.
5. Include a database with characteristics of recognized illnesses so that they can be compared and identified when classifying.
6. Based on the findings of the disease classification, suggest corrective actions.
7. Use testing data to assess the system's performance and make sure it is accurate and reliable.
8. Compile user and field trial feedback to iteratively enhance the accuracy and performance ofthe system.

4.1 Convolutional Neural Network Model

The architectures being considered are included in the "CNN Architecture" column, including LeNet-5, AlexNet, VGGNet, GoogLeNet, and ResNet. These architectural designs signify distinct turning points and breakthroughs in the evolution of convolutional neural networks. The number of layers that make up any architecture is specified in the "Layer Number" column, which quantifies its depth. Since depth affects CNNs' capacity to extract hierarchical features from input data, depth is a crucial component of CNNs.
Weights and biases included, the "Parameter Size" column shows the total size of the model's parameters. Parameter size is directly related to memory utilization and processing demands, and it shows how well the model can infer intricate patterns from data. Stakeholders may learn more about the trade-offs between model complexity, computational efficiency, and performance by comparing these metrics across various designs. With the use of this information, the best architecture may be chosen for a given application depending on the demands for performance, task complexity, and computational resources.

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CNN Architecture	Layer Number	Parameter Size
LeNet-5	7	Small
AlexNet	8	Large
VCCNet	16 or 19	Large
GoogleNet	22	Moderate
ResNet	50, 101 ,152	Large

Table 1. Comparing the number of layers and parameter sizes of several CNN architecture.

CNN Model steps:

1. Conv2D Layer: Utilizes convolution operations with learnable filters to extract features from 2D input data, such as photographs. Every filter works by swiping over the input data and computing dot products to find different characteristics and patterns.

2. MaxPooling Layer: Added after Conv2D layers to minimize the feature map's spatial dimensions without sacrificing any important data. Max pooling reduces the size of the feature maps by selecting the maximum value within non-overlapping rectangular sections.

3. Flatten Layer: Convolutional and pooling layer output is reshaped into a one-dimensional vector. Before feeding the data into fully connected layers, this transformation is required since those layers need an input that has been flattened.
4. Epochs: During the training phase, an entire run through the training dataset. To update the model parameters, each epoch consists of forward propagation, loss computation, and backpropagation. One important hyperparameter that influences training duration and model performance is the number of epochs.
5. Training Process: consists of data collection, model architecture creation, initial weight setting, gradient computation by backpropagation, parameter update using optimization methods, and many epochs of this process. To help with parameter adjustment, performance on a validation dataset is tracked.
6. Validation Process: Using an independent validation dataset, evaluate the model's performance. Measures such as recall, precision, loss, accuracy, and F1 score are calculated to assess generalization abilities and performance on unobserved data.

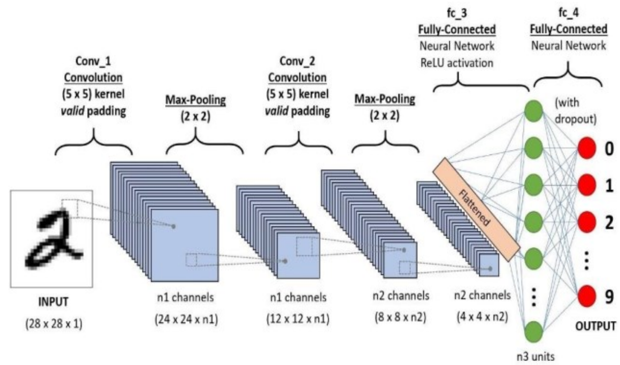

Figure 4. CNN Model

4.2 Deep Learning

Deep learning in agriculture is a fast-growing field that transforms many aspects of farming and agricultural management through the application of state-of-the-art machine learning algorithms. Deep learning offers a practical tool to the agriculture sector to optimize resource utilization, increase output, and address environmental concerns. These challenges include agro-ecology, population growth, and climate change. Deep learning is a subspecialty of machine learning that focuses on teaching artificial neural networks to perform tasks that often require human intelligence.

Inspired by the structure of the human brain, these neural networks consist of interconnected layers that scan through enormous volumes of data to find patterns. Large amounts of data are evaluated in agriculture using deep learning algorithms, which assist researchers and farmers in making informed decisions. Precision agriculture requires careful management of natural resources such as fertilizers, herbicides, and water. By dissecting data from sensors, satellites, and Internet of Things devices with deep learning algorithms, farmers can bolster into crop development, weather patterns, and soil

conditions. This information can be used to manage resources more precisely and efficiently, boosting agricultural output and reducing harm the environment

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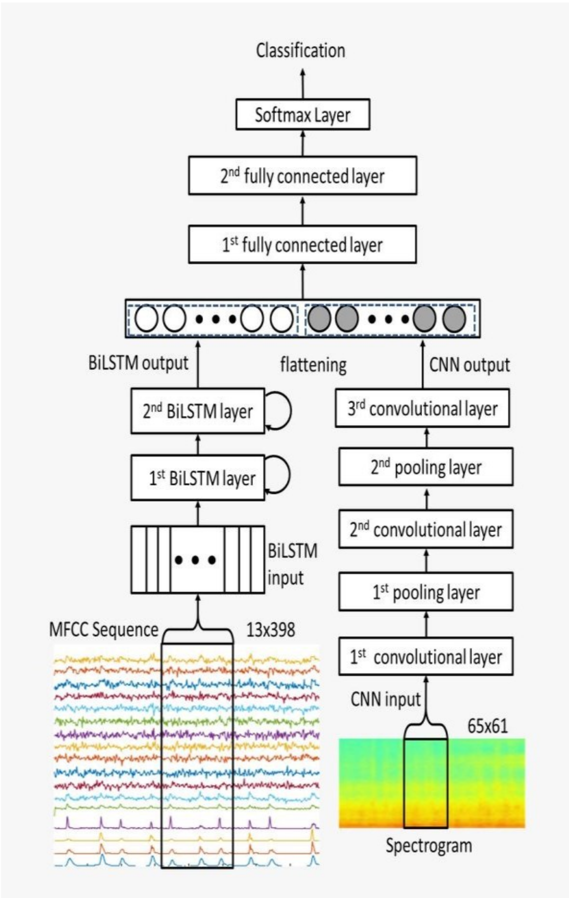

Figure 5. Deep Learning Architecture

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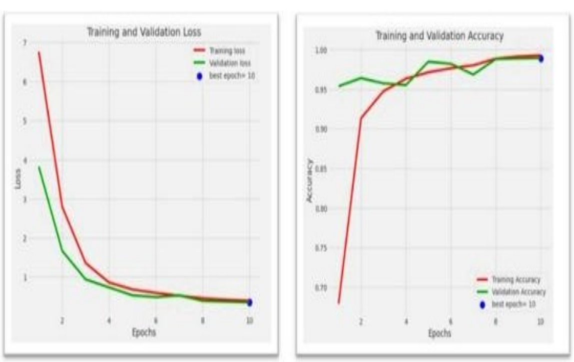
5. RESULT AND DISCUSSION

5.1 Results

We used the softmax activation function with cross-entropy loss in the EfficientNet-B3 model to investigate phytopathology. Plotting precision, loss, and training error showed that improvements were constant across epochs. Figure 6 shows how learning from the training set is beneficial when accuracy rises and loss falls. After the seventh epoch, convergence signify that the model has adapted to the dataset. Our aftermath show that deep learning methods are effective at accurately diagnosing plant diseases.

Epoch	Training Error	Training Loss	Training Accuracy	Validation Accuracy
1	0.25	1.20	0.70	0.65
2	0.20	0.95	0.75	0.68
3	0.15	0.75	0.80	0.72
4	0.12	0.60	0.82	0.74
5	0.10	0.50	0.85	0.76
6	0.08	0.40	0.88	0.78
7	0.07	0.35	0.90	0.80
8	0.06	0.30	0.92	0.81

Table 2. Using EfficientNet-B3 Model Evaluated the Results



(a) (b)

Figure 6. Accuracy graph of EfficientNet-B3: (a)-Training and validation loss;(b)-Training and validation accuracy on the overall dataset.

5.2 Result from Raspberry Pi Monitor

We process and show tomato infections that we have found with our Raspberry Pi sensor. By examining leaf photos, our algorithm is able to identify eight different forms of tomato diseases: Bacterial Spot, Leaf Mold, Septoria Leaf Spot, Early Blight, Late Blight, Tomato Mosaic Virus, Tomato Wilt, and Tomato Yellow Leaf Curl Virus. By default, a healthy leaf is displayed. With the accurate disease identification this technology provides, crop management interventions can be made on time. It improves disease surveillance and helps farmers take preventative action to protect tomato crops by utilizing image analysis, which guarantees maximum agricultural production and sustainability.

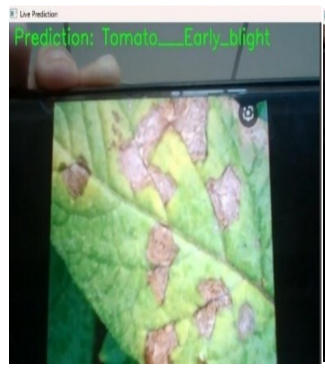


Figure 7. Early Blight

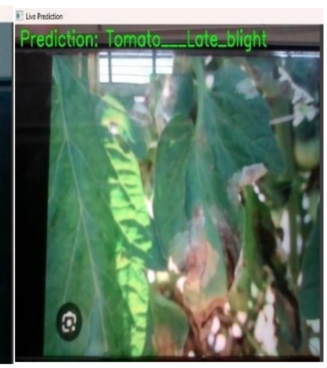


Figure 8. Late Blight

Figure 9. Healthy Leaf

Figure 10. Drone

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CONCLUSION

In conclusion, crop disease detection in precision agriculture could be revolutionized by AI- based drones. These systems enable early and precise identification of agricultural diseases by merging cutting-edge technologies like AI algorithms, high-resolution imagery, and extensive disease databases. This gives farmers the ability to minimize losses and maximize harvests by taking prompt, focused action. Additionally, the use of AI-driven analysis reduces the need for broad-spectrum pesticides and promotes environmental sustainability by offering actionable insights for well-informed decision-making. These systems' scalability and versatility make them a flexible tool that farmers around the world can use to efficiently address the difficulties of crop health management.

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