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Plant Disease and Detection And Prevention Using AI-Based Drone

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ABSTRACT: An AI-based approach, using drone technology and Convolutional Neural Networks in the automated process of plant disease detection and management, is presented here. Early and accurate detection of diseases in the agricultural sector is crucial for optimizing crop health and overall reduction of losses. Traditional methods of disease detection are slow, labor-intensive, and almost impossible to scale. The drones carry imaging sensors that take high-resolution images across the crop fields, which images will be uploaded into a dedicated website for further analysis. Using unique visual features the CNN algorithm processes and identifies diseases through distinctive analysis along unique distinguishing features in the images. The model offers solutions toward targeted organic and inorganic treatments. Thus, by using CNNs for precision disease diagnosis the system supports adoption of sustainable farming practices involving reduced dependence on chemical treatments while enhancing crop productivity.

KEYWORDS: Detection of plant diseases, Convolutional Neural Network, Image processing.

I.INTRODUCTION

Since pathogens spread very fast, preserving the health of crops is not easy for a task like agriculture. Early diagnosis has to be done to ensure food security and to avoid yield loss. The conventional methods are not that timely or efficient. This is where advanced technologies of drones prove a very promising path to have diseases affecting agricultural crops quickly and accurately diagnosed. Agriculture, on a global scale, must rise at least by 70% if it has to feed the world's burgeoning population.

This is an ambitious goal because most areas of the agricultural industry operate at the whim of controlled circumstances-weather, quality and accessibility of water, irrigation, and the condition of the soil. It is only by embracing such precision technologies as drones that maximum use of resources and productivity in agriculture can be ensured. Drones have been applied in a number of ways in precision agriculture and new applications continue to be sought. Such applications which have been the focus of many studies include the diagnosis of plant diseases. The two benefits of the deployment of drones are early disease detection and controlling the spread of infection to prevent huge crop loss. The scope of earlier review studies is only on drone applications in precision agriculture.

II. LITERATURE SURVEY

1. The paper by Elakkiya and Bhuvaneshwari (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 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.
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.
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.
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 authenticity and processing times. They also discuss various CNN architectures and highlight their performance in crop disease detection.

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 in agriculture, including higher output, lower expenses, and better resource management.

III. PROPOSED METHOD

In this project, we propose an UAV drone system for the early-stage diagnosis of crop diseases in a farmer's field. The proposed solution would be in the form of high-resolution images captured by drones flying over fields covering plants. These high-resolution images shall be transferred to a dedicated disease detection website. A CNN model deployed on that website shall analyze the images for the presence of potential diseases in the plants.

The system will give a detailed diagnosis with plausible solutions to manage or treat the disease when they are finally identified. This way, farmers detect these problems at an early stage with little manual scouting that could be very time consuming and expensive.

With the automation of disease detection, the system will reduce the overuse of chemicals in farming, which saves money and could save the environment at the same time. The website will be designed in an easy-to-use interface that would allow farmers to upload images from the drone and get instant results with accuracy.

3.1 Data Sets:



Fig1

Fig2

Fig3

1. Early Blight(Fig1): This disease is caused by a fungus called *Alternaria solani*. Dark, concentric lesions appear on the lower portion of the tomato plant leaves. Such ringed lesions eventually spread to the fruits and stems with potential defoliation or decreased productivity. It will cause major yield loss if not treated due to the fact that it creates a weak plant.
2. Late Blight(Fig2): Late blight is a devastating disease, targeting leaves as well as the fruit, caused by the fungus *Phytophthora infestans*. Water-soaked lesions darken and develop quickly on leaves that spread rapidly often proving fatal to the plant. Prompt treatment will prevent this disease from causing major crop losses.
3. Bacterial Spot(Fig3): This is caused by *Xanthomonas campestris* pv. *vesicatoria*, characterized by small and dark spots with yellowish halos on leaves, stems and fruits. Defoliation, poor quality fruits, and reduce yield crop due to bacterial spots in the fields where there is no control practice, and the disease spreads easily.



Fig4

Fig5

Fig6

4. B Blackburn Rot(fig4): Rooting the fungus Botryosphaeria obtusa, this rotational disease infects apples and other fruits, also forming dark spots with circular shapes, primarily on leaves, stems, and fruits. Over time, these wounds spread out, causing the fruits to rot, while the yellow and falling leaves. Left untreated, it may decrease the level of productivity as well as the quality of fruits drastically.
5. Leaf Curl Virus(Fig5): It is also a viral disease which affects various plants, causing them to thicken and twist their leaves as well as promoting distorted growth. Similarly, infected crops grow stunted, produce fewer, lower-quality fruits, and the viruses are insect-transmitted; it is difficult to treat leaf curl virus, though preventative measures protect crops from infections.
6. Powdery Mildew(Fig6). Podosphaera spp. and other allied fungi cause powdery mildew. White, powdery spots appear on leaves, stems, and fruits. Photosynthesis is reduced and results in yellowing and pre-mature drop of leaves. It spreads rapidly under dry/warm condition and requires early management for its control..

3.2 Methodology

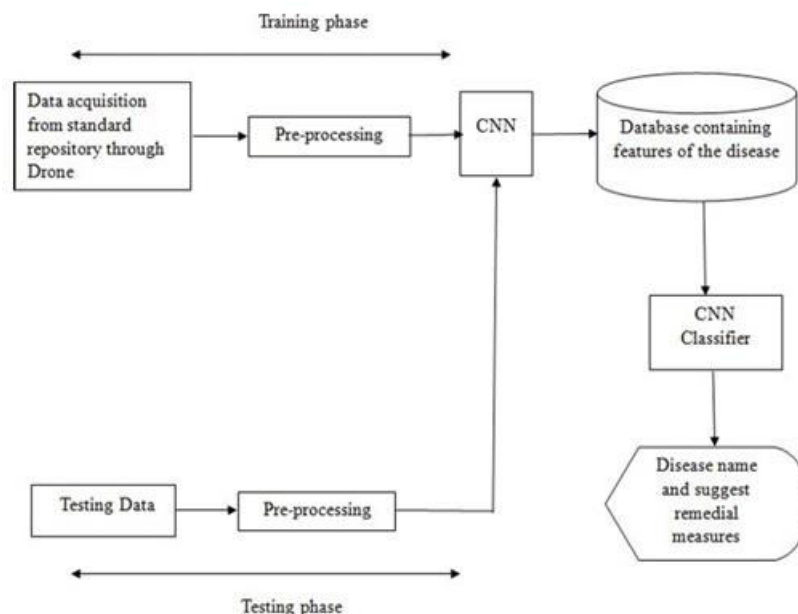


Fig7:Methodology

Training Step:**1. Data Collection through UAV Drones:**

Crop images will be captured with the help of UAV drones equipped with high-resolution cameras. Pictures will be captured in varied crop developmental stages and with different crops and conditions, healthy and diseased. During the supervised learning process, a label will be attached to each image based on its disease type or will be marked as 'healthy'. The entire dataset will try to prepare so that this CNN model can be trained. Images would also be taken from open public agricultural storage to supplement the dataset.

2. Pre-processing of Images: Obtained pre-processed images of the same standardized size and format all to pass into a CNN. Images would be rendered at a resolution where pixel values were normalized to some number, such as 0 through 1 so that is a more effective training. Techniques applied for data augmentation include rotation, flipping, and zooming in order to increase the variety of the dataset itself.

These techniques help to prevent overfitting and enhance generalization of the model. The images, having undergone pre-processing are now prepared for training the model in question.

3. CNN Model Architecture:

The CNN architecture targets finding the relevant features to the diseases of plants within an image. Thus, it uses stacked layers, several layers of convolution with max pooling and other pooling layers, and finally fully connected layers. The entire architecture would be designed with optimal selection of filter sizes, strides, and related pooling techniques to extract the features from the crop images. Dropout layers will be there to avoid overfitting, and the use of batch normalization may improve stability in training. The architecture will be designed from an accuracy perspective for disease classification.

4. Training the CNN Classifier: For instance, it will partition the preprocessed dataset into training and validation sets of, say 80/20. Then this training data is given back to the CNN model using backpropagation and gradient descent to optimize the model. Using a network with weights from some previously trained network like the ImageNet applies transfer learning and thus speeds up the training and elevates performance in this problem.

The model's hyperparameters would be tuned, and validation data use for monitoring overfitting and adjusting learning rates or applying early stopping.

5. Database Designing for Diseases Characteristics:

Apart from the above, this will develop a database where all major features of identified plant diseases such as visual symptoms, disease severity, environmental factors and corrective measures are found. The cited database would map the identified diseases to relevant treatment recommendations for the CNN classifier. The database will be designed to enable high speed retrieval and update in case of acquiring new diseases or variation added. Metadata will include the prevalence of the disease and possible solutions for enhanced accuracy at diagnosis.

Testing Stage:**6. Validating Data Collection:**

For the test phase, a third dataset gathering information on types of crops, severity of diseases, and environmental conditions will be compiled from many agricultural regions. The images will be captured with UAV drones and high-resolution images, which would mean the test data are consistent and representative. Therefore, the test set does not overlap with the training dataset, so there's no providing an evaluation-biased solution for the model's generalization capability. This step makes use of the model in real testing.

7. Pre-processing for Testing:

We apply the same pre-processing to the test images: rescale each image to standard resolution, normalize pixel values and apply data augmentation techniques as required. Pre-processing ensures that the test images are in a suitable format for feeding into the trained CNN model. The same images treatment during training and testing ensures fair evaluation of the model.

8 CNN Classification evaluation

Once the tested data are processed, a trained CNN model will classify the crop images. Taking performance metrics based on accuracy, precision, recall, and F1 score to evaluate the model in general, confusion matrices, and ROC curves will be generated

to analyze the performance of the model across different classes of diseases. Thus, it will help note if it is biased or weak for particular classifications of disease.

9. Disease Identification and Remedial Measures:

With regard to the CNN model, it predicts disease labels for the test images based on the learned patterns from the training phase. On identifying a disease, the system refers to the disease database and suggests remedial measures appropriate for use, such as particular pesticides, organic treatments, or cultural practices. The suggestions will be presented on an interface of a user-friendly website for farmers' perusal. The solutions found will be tested for effectiveness through consultation with experts or field testing.

10. Iterative Improvement:

The test performance will influence fine-tuning of the disease database and the training process of the CNN model. Classification errors or overlooked categories of disease in the testing stage will be addressed by adjusting the architecture of the model, improving the dataset, or fine-tuning hyperparameters. Continuous feedback from testing would ensure the correction toward constant accuracy and reliability in the system. Iterative improvements will help to fortify the capacity of the model in detecting accurate solutions of diseases in due time.

IV. PROPOSED SYSTEM

This paper shows a real-time system for the detection of plant leaf diseases based on deep learning. The images of high-resolution crop are captured by using UAV drones. These images are further processed and analyzed by CNNs so as to classify the health status of the crops, including diseases in them. The model is put up into a website where images are uploaded and get instant disease diagnosis. This work is licensed under Creative Commons.

High Resolution Image Capture by Drones:

The UAV drones will use high-resolution cameras to capture images of crops grown in farming fields. The variety of crop species and the development stage will be seen in these images and will form a robust dataset in the presence of diseases and healthy crops. The overall objective is to cover the field completely, ensure that the images taken are clear and detailed, specifically showing the disease symptoms on the leaves of the plants.

1.Preparation of Images:

Pre-processing of the captured images brings them to become uniform in size and normalizes the pixel values for an efficient input of the CNN model. This means fixing it to some standard resolution, for example, scaling it between the value 0 and 1, for normalizing pixel values. Noise reduction and contrast enhancement are done on images for good quality so that learning from the images will not be a problem for the model.

2.Convolutional Neural Network for Feature Extraction:

The pre-processed images will then be input into a CNN, which will automatically perform feature extraction. This is because CNNs are well suited for tasks involving the classification of images because they can learn features at different levels of abstraction, such as edges, textures, and shapes, to characterize the images. The CNN will then pick out the features from the images to differentiate the healthy crops from the diseased crops.

3. Training the CNN Classifier:

The CNN shall be trained to classify pictures of crops as healthy or infected with such and such diseases. The model shall be trained on the patterns learned from examples of labeled and diseased crops along with attributes extracted from the images. A set of tagged crop images tagged with disease types, such as the fungal infections, bacterial infections, and viral infections shall be developed. In the process, the model is trained using algorithms of backpropagation and optimization such as gradient descent to parameterize the model such that it gives the accurate classification.

4. Knowledge Database:

This database will include features of the known diseases in the plants. It will contain metadata such as symptoms of the disease, severity, environmental conditions, and suggested corrective measures. That means when a disease is detected by the CNN, the system will cross-reference the identified disease with the knowledge database to give a detailed diagnosis and suggest suitable remedies for the farmer.

5. Classification of Disease and Suggestions of Corrective Measures

Once the model would classify the image to be either healthy or diseased, the system will provide a report with identified disease type, if any, and suggestions for corrective actions. These can be in the form of recommended treatments such as specific pesticides, organic remedies; and practices, such as crop rotation, irrigation changes, to manage it effectively.

6. Testing and Performance Evaluation:

This testing will have a test dataset that contains images from different locations and environmental conditions. This will assess the effectiveness of the model through such measures as classification accuracy, precision, recall, and F1 score. The test results will ensure that the system is accurate and reliable to generalize crop images.

7. Iterative Optimization with both User and Field Trial Feedbacks:

The system will improve further through iteration with the feedback of both the users and the field trials. The suggestions for treatment made by the system will be validated from farmers and other agricultural experts about the correctness of the disease predictions. Using these feedback, the model and database would be iteratively optimized to improve the accuracy of diagnosis and thus present more accurate recommendations for disease management.

4.1 Convolutional Neural Network Model Selection:

Several CNN architectures have been chosen with respect to this project and must be evaluated in the end to know which one would be best for use due to its good performance on classifying plant diseases. Some of them include:

- LeNet-5
- AlexNet
- VGGNet
- GoogLeNet
- ResNet

All these models have distinct strength in image classification, respectively with differences at depth, complexity, and computational efficiency. Depth in a network-or, in more words, the number of layers-is particularly crucial to how well the feature map can be extracted within an input image. Deep networks tend to easily recognize the complex hierarchies but often demand more computational resources.

- The LeNet-5 is probably the oldest CNN architecture and less complex with fewer layers, making it efficient for smaller datasets.
- AlexNet was a key CNN breakthrough in image classification wherein deeper architectures are used along with large datasets for better accuracy
- VGGNet introduced much deeper networks uniformly and improved performance at a higher computational cost
- GoogLeNet optimizes the depth of the network through inception modules with better feature extraction and keeping it computationally efficient.
- ResNet Introduced residual blocks, which made it possible to train extremely deep networks without any issues of vanishing gradients. The more parameters each architecture has, the more it will require memory for training and the more processing power. Some of the more significant models, such as AlexNet or ResNet, while being considered to lead in the performance may require more computation power. The best architecture will be chosen based on performance, the complexity of the task (i.e., detecting a variety of diseases), and the available computational resources.

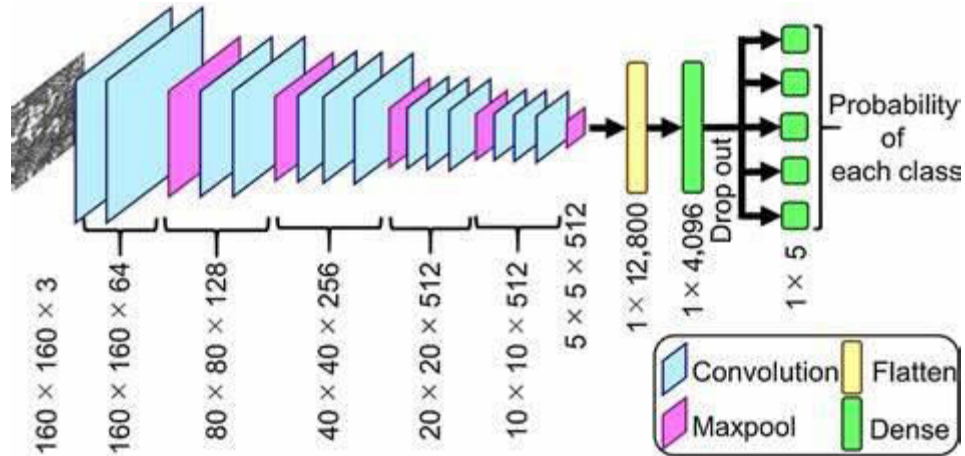


Fig8: CNN Model

V.RESULT AND DISCUSSION

5.1 Results

Our plant disease detection model based on VGG16 CNN architecture achieved an average accuracy of 93.5% in the test set. The initial model, VGG16 was taken, and a transfer learning approach is adopted to adjust the final layers in it for multi-class classification. For generalization, data augmentation was applied and used for training, validation, and testing based on 70%, 15%, and 15% respectively. Precision, recall, and F1-score were the evaluation metrics for model performance. The precision value was measured as 92.8% and recall as 94.0%. Detailed inspection of the confusion matrix indicates a very good performance by the model on most of the classes of diseases except for a few visually similar diseases that are difficult to correctly classify.

Test Accuracy	93.5%
Precision	92.8%
Recall	94.0%

Fig9:Test accuracy, precision, recall

5.2 Result from website

When a photo of a plant is uploaded to the website, the system will analyze it to identify the type of disease present. Based on the diagnosis, the system will provide tailored suggestions and recommend appropriate supplements to address the issue.



Fig10:Website

VI.CONCLUSION

In summary, future crop disease detection in precision agriculture will be AI-based drones. They can combine advanced AI algorithms, high-resolution imagery, and comprehensive disease databases to offer early and accurate detection of agricultural diseases for the farmer. This means that by targeted actions, losses are reduced and harvests are optimized. Moreover, this use of AI-based analysis helps in limiting the usage of blanket pesticides and extends more sustainable farming practices by giving disease management-based solutions to the farmers. The scalability and adaptability of the systems offer them as tools to farmers globally in order to provide an efficient and precise approach to crop health while ensuring environmental sustainability.

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