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Plant Species Health Detection Using Artificial Intelligence

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Abstract
Plants health detection is essential in maintaining agricultural output and sustainable environment. This study examines the utilization of Artificial Intelligence (AI) algorithms in automating plant health analysis. the system scans plant images in search of diseases, nutrients, and stress levels. The proposed solution integrates computer vision and machine learning models, which are trained across different datasets and include both samples of healthy and ill plants. The AI detection system enhances early diagnosis such that intervention is done on time and crops are not lost. The research shows the accuracy of AI in measuring plant health, providing a valuable and scalable procedure for both scientists and farmers. Our system makes use of Convolutional Neural Networks and deep learning techniques trained on huge sets of images of plants with both healthy and sick examples. By analyzing leaf shapes, color patterns, and distorted shapes, the AI model can accurately classify plant conditions, including diseases such as bacterial infections, fungal infestation, and starvation for nutrients. The system is designed for early plant disease detection, allowing farmers to intervene in time and minimize financial losses. Future developments involve the integration of Internet of Things (IoT) sensors for real-time sensing and a broader range of plant species for the model.
Keywords: *Plant Health Detection, Artificial Intelligence, Deep Learning, Convolutional Neural Networks (CNNs), Plant Disease Classification, Automated Diagnosis, Image Processing, Smart Farming.*

1. Introduction
Agriculture is a crucial sector of India's economy, as it employs more than 50% of the population and contributes about 18-20% to the nation's GDP. But the agricultural sector has various problems, including inefficient agricultural practices, poor fertilizer application, water shortages, and plant pathologies. Plant pathogens are the primary contributors of crop losses, which reach as much as 30% of crops. Plant disease manual identification is time-consuming and not accurate, and there is a pressing need for breakthrough solutions. we utilized drones and high-definition cameras for image capturing of different plant species in natural agricultural settings. Utilizing drones offers superior advantages, with large-scale fields monitored from various angles and heights, guaranteeing complete coverage and taking pictures that otherwise may be difficult to observe through manual inspection [1]. Herein, we suggest an AI-enabled method for the detection of plant species health using image data with a specific focus on the diagnosis and classification of plant health based on plant images. We use state-of-the-art convolutional neural networks (CNNs) and transfer learning methods to learn strong models with the ability to classify and recognize multiple plant species and their associated health conditions accurately. The system intended has the aim to offer a clever, expandable, and budget-friendly system for early illness recognition and crop wellbeing monitoring in environmental and farming

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scenarios. Technological advancements have created opportunities for precise detection and identification of plant diseases, paving the way for improved treatment. This system identifies 14 types of plant diseases, such as apple, blueberry, cherry, corn, grape, orange, peach, pepper, potato, raspberry, soybean, squash, strawberry, and tomato, through the use of deep learning methods, specifically convolutional neural networks (CNN). The system uses a statistical model that takes input images and classifies output tags through processing, giving a sound solution for plant disease detection. Figure 1 shows Steps for diagnosis & classification of plant leaf diseases.

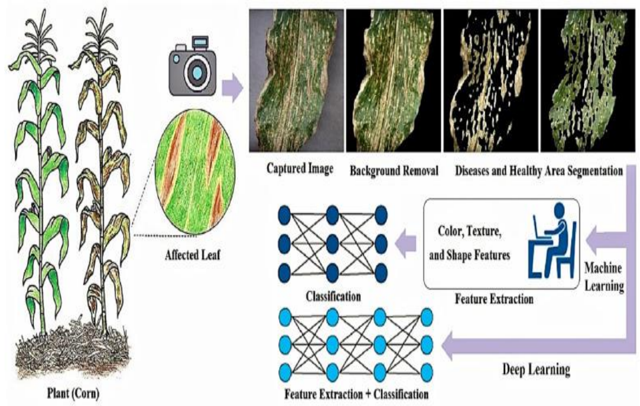

Figure 1 **Steps for Diagnosis & Classification of Plant Leaf Diseases**

2. Proposed Method

In the present study, a disease-detecting model for rice plants has been established based on AI with the help of Convolutional Neural Networks (CNN) with the VGG16 architecture. It is made to analyze plant images automatically, identify major features, and categorize them as healthy or diseased. The procedure starts with image gathering via drones and high-resolution cameras, which record varied images from all directions and conditions in the field. Post-acquisition, the images are processed to eliminate noise, normalize sizes, and improve quality for better model performance. The preprocessed images are subsequently input into the VGG16 model, which is an effective feature extractor owing to its deep layer structure and capacity to extract intricate visual patterns. The convolutional layers are able to detect features like color transitions, texture variations in leaves, and apparent disease symptoms. These characteristics are subsequently fed through fully connected layers, wherein the classification occurs and the species of plant as well as the nature of disease is identified. This CNN-based system, based on VGG16, presents a sound and consistent aid for early diagnosis of rice plant diseases to assist with precision agriculture and enhance crop productivity. Figure 2 shows Vgg16 Model. [2]

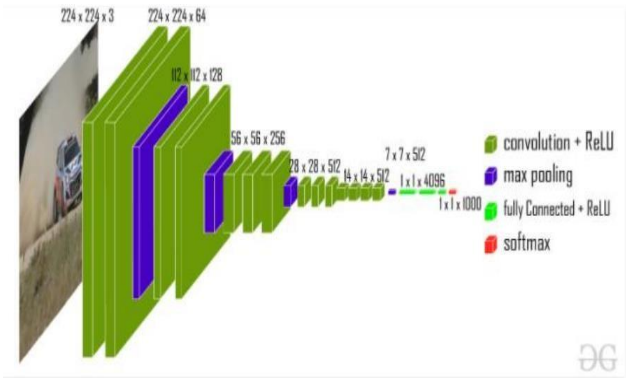

Figure 2 **VGG 16 Model**

These features extracted are used to enable the model to learn patterns that differentiate between healthy and diseased rice plants. The classification is finally done by the fully connected layers of the network, leading to precise detection of the plant health status. This method not only improves the speed and accuracy of disease detection but also offers a scalable and dependable solution for smart farming and agricultural surveillance. Figure 3 shows CNN Architecture [6].

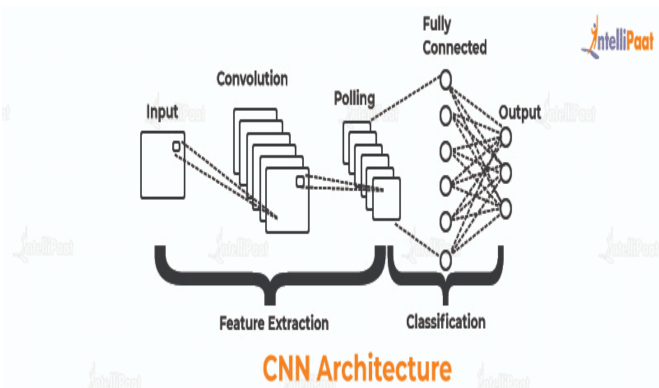

Figure 3 **CNN Architecture**

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2.1 Data Preparation

A model for detecting rice plant diseases using CNN and VGG16 algorithms has been proposed with a series of steps. First, a dataset of healthy and diseased rice plant images with various diseases labeled will be collected. Then, the dataset will be preprocessed by resizing the images, normalizing pixel values, and applying data augmentation techniques. The dataset will be split into training, validation, and test sets. The VGG16 architecture will be chosen as the base model for the CNN, and fine-tuning will be performed by freezing some layers and adding custom layers for disease classification. The model will be trained on the training set using the Adam optimizer and categorical cross-entropy loss function, for an appropriate number of epochs to achieve good performance on the validation set. The trained model will then be evaluated on the test set using metrics such as accuracy, precision, recall, and F1 score. Finally, the model will be deployed for use in real-world applications, such as an app for farmers to identify rice plant diseases. This proposed model has the potential to aid farmers in the early detection and treatment of rice plant diseases, leading to increased crop yields and food security [4].

2.2 VGG16 Architecture

VGG16 is a very popular deep learning model in the Convolutional Neural Network (CNN) family. The VGG16 model was first released by the Visual Geometry Group at Oxford University. VGG16 is renowned for being very simple, deep, and performing amazingly well in image classification problems. "16" in the name VGG16 signifies that the model consists of a total of 16 weight layers 13 convolution layers and 3 fully connected layers. The VGG16 architecture is constructed using small (3x3) filters with stride and padding of 1, and 2x2 max-pooling layers, which reduce the spatial dimensions while retaining key features. VGG16 became popular for its capability to learn difficult and hierarchical features from images. It is generally utilized as a backbone for many computer visions tasks, such as object detection, image classification, and medical and agricultural diagnostics, by utilizing full training or transfer learning methods. Figure 9 shows Soyabean Healthy.

2.3 Working of VGG16 Model

- **Block 1** — Simple pattern detection (edges, lines)
- **Layer 1 (Conv)** — Identifies very simple features such as horizontal and vertical edges.
- **Layer 2 (Conv)** — Enhances edge detection and begins to identify simple textures.
- **Block 2** — Detecting simple shapes and corners
- **Layer 3 (Conv)** — Identifies slightly more intricate features such as corners and contours.
- **Layer 4 (Conv)** — Refines previous patterns and begins to identify local structures.
- **Block 3** — Detecting shapes (textures)
- **Layer 5 (Conv)** — Detects more complicated patterns, such as leaf texture.
- **Layer 6 (Conv)** — Merges various texture features.
- **Layer 7 (Conv)** — Begins to recognize complicated parts of objects (leaf patterns, spots).
- **Block 4** — Detecting object parts (leaf patterns, disease spots)
- **Layer 8 (Conv)** — Detects parts of objects, such as big patches or unpredictable patterns.
- **Layer 9 (Conv)** — Fines fine details of parts of objects and starts to make sense of structures in plants.
- **Layer 10 (Conv)** — Merges several parts together into larger structures (intact diseased areas).
- **Block 5** — Detection of detailed structures (hints about disease types)
- **Layer 11 (Conv)** — Starts identifying complete structures like full leaves or large regions of disease.
- **Layer 12 (Conv)** — Refines complete structures and starts distinguishing health from unhealth.
- **Layer 13 (Conv)** — Last feature extraction layer that is used to prepare data for classification.
- **Fully Connected Layers** — Decision making component
- **Layer 14 (Fully Connected)** — Utilizes extracted features to begin making decisions; identifies relationships between features.
- **Layer 15 (Fully Connected)** — Combines those

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relationships further and gets ready for final decision.

- **Layer 16 (Fully Connected + SoftMax) —** Outputs final classification output: assigns probability to every class (disease or healthy). Figure 7 shows Berry healthy [5].

2.4 VGG16Training

To identify the leaves of apple, tomato, grapes, blueberry, potato, soybean, and strawberry plants as healthy or unhealthy through a deep learning model (VGG16). we gathered a big dataset of leaf images for apple, tomato, grapes, blueberry, potato, soybean, and strawberry plants. Both healthy and unhealthy leaf images were present in each category. our leaf images initially to 224x224 pixels and Once we had the model established, we resized each of normalized (scaled pixel values between 0 and 1). The VGG16 model processed these images through several layers: Firstly, the image passed through convolutional layers that identified edges, texture, and patterns on the leaf. Then, ReLU activation functions assisted the model in learning non-linear features, such as spots, color transitions, and disease patterns. Subsequently, the images were subjected to max pooling layers, which contracted the dimensions without losing the critical features. These steps were iterated across 13 convolutional and 5 max-pooling layers. Feature extraction was followed by the feature output, which was flattened and sent to dense layers that I inserted, which learned to map the extracted features to healthy or unhealthy classes. Figure 8 shows Potato Unhealthy. Lastly, a SoftMax activation function created the prediction probability of both classes (unhealthy or healthy) and the one with the largest probability was regarded as the prediction of the model. I was keeping track of the training via checking the graphs of the accuracy and loss of the model with respect to training and validation data sets. [3]

3. Results

Once the training was over, I ran new unseen leaf images and the model correctly classified them. Some of the results I saw:

- An apple leaf with fungal brown spots was marked as unhealthy. Figure 4 shows Apple unhealthy.
- A tomato leaf with vibrant green, even color was marked as healthy.
- A grape leaf with yellow spots that could be seen was marked as unhealthy.
- A blueberry leaf with no discoloration or damage was marked as healthy.
- A potato leaf exhibiting curling and black blisters was rated as unhealthy.
- A soybean leaf with no damage visible was rated as healthy.
- A strawberry leaf exhibiting powdery mildew was rated as unhealthy. Figure 5 shows Tomato healthy.

Conclusion: Using the VGG16 model and transfer learning, I could accurately classify images of apple leaves, tomato leaves, grapes leaves, blueberry leaves, potato leaves, soybean leaves, and strawberry leaves as healthy or unhealthy. The model was able to extract crucial features from each leaf image efficiently and showed great accuracy in the identification of leaf health status. This method can assist in the early detection of plant diseases and can be used as a beneficial tool for farmers and agricultural scientists. Figure 6 shows Grape Unhealthy.

Figure 4 Apple Unhealthy

Figure 5 Tomato Healthy

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Figure 6 Grape Unhealthy

Figure 7 Berry Healthy

Figure 8 Potato Unhealthy

Figure 9 Soya Bean Healthy

Figure 10 Strawberry Unhealthy

Conclusions

Using the VGG16 model and transfer learning, we were able to classify leaf images of apple, tomato, grapes, blueberry, potato, soybean, and strawberry as healthy or unhealthy. The model was able to extract significant features from every image and showed high accuracy in identifying leaf health conditions. This method can be used for early detection of plant diseases and can be a useful tool for farmers and agricultural scientists. Figure 10 shows Strawberry Unhealthy.

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