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Plant Leaf Diseases Prediction: Using Machine Learning

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Abstract- This study investigates the monitoring of progressive compressive strength development in concrete using non-destructive testing (NDT) techniques, aiming to provide a reliable, in-situ alternative to traditional destructive testing. An experimental program was conducted on concrete specimens (mixes with varying strength ranges) to track strength evolution at early and mature ages, specifically 7, 28, and 90 days. The NDT techniques, primarily focusing on Ultrasonic Pulse Velocity (UPV) and the Rebound Hammer (RH) test, were utilized to estimate the compressive strength (SonReb method). The research confirms that while sole NDT methods possess inherent inaccuracies (roughly $\pm$15-20% for RH), combining RH and UPV significantly improves the precision of in-situ concrete strength predictions.This study presents a systematic investigation of the monitoring of progressive compressive strength of M30 Concrete using a pendulum-based non-destructive testing (NDT) technique. The research is based on the principle of the coefficient of restitution, where the rebound angle of a pendulum after impact is correlated with the compressive strength of concrete. Traditional strength evaluation using the Compression Testing Machine (CTM) is destructive and unsuitable for in-situ monitoring. To overcome this limitation, a pendulum-based device is used to measure rebound angle at different curing ages (2, 7, 14, 21, and 28 days).Two empirical relationships were developed 1) Y= -0.0867x^2+12.318x-405.74 2) Y= 0.0028x^2+0.2613x+56.976 where x is the rebound angle, and Y is the compressive strength (MPa). The results show a strong correlation between rebound angle and compressive strength, validating the effectiveness of the proposed method. The study demonstrates that this technique is economical, simple, and suitable for real-time field applications.

Keywords: Rebound Angle. Compressive Strength. Correlation. Strength Prediction.

I. INTRODUCTION

The proposed system integrates both feature-based and network-based anomaly detection, leveraging the interaction between entities and their attributes to uncover hidden patterns associated with fraud [1]. Plant diseases cause significant reductions in plant production, leading to significant economic losses [2]. Today, the goal of digital picture tampering detection is to guarantee the consistency and dependability of digital photographs. Maintaining the integrity of digital content is very important in different domains such as journalism, media, social media, forensics, and national security [3].

ML has been shown to be a significant tool for heart disease prediction and management using complex algorithms to analyze complicated data and the choice of high-risk factors [4]. In most networks, the vast majority of data consists of normal user activities, while malicious attempts represent a tiny fraction [5]. While key advancements such as NLP and neural networks enable extraction of meaning in content, authorship, and user behavior in very complex patterns, issues related to data bias, the degree of algorithmic transparency, and more intelligent tactics of misinformation remain [6], [1].

Such infections have no clear effects, or the result becomes apparent too late to intervene, necessitating a thorough investigation. Most illnesses, on the other hand, induce some manifestation as a result, the main method used in use for plant disease diagnosis is a qualified professional's unaided eye examination [7].

A plant pathologist must have good observing skills to recognize signature signs and identify plant diseases reliably . And this mostly happens to farmers with fewer resources in developing counties. They generate almost more than eighty of the agricultural production [8]. To overcome these limitations, technology-based solutions such as machine learning (ML) and artificial intelligence (AI) have been used in agriculture, offering a data- driven solution to crop prediction, yield forecasting, and plant disease detection [9].

The leaf's differently coloured spots and patterns are highly efficient in finding the disease . Infected plants demonstrate a variety of symptoms such as coloured spots or lines on the leaves, roots, and seeds . Disease detection and identification in plants can be performed using direct and indirect approaches. Because large amounts ofsamples are to be processed, molecular and serological techniques for direct detection of diseases can be used for detailed analysis [10]. There are many traditional approaches like the use of pesticides to prevent crop loss which happens due to diseases have become very common but identifying the type of disease on time and accurately can help better deal with the problem effectively using fewer resources [11].

The traditional disease identification approach is mostly manual by the plant disease specialists such as agricultural engineers and botanists. Traditional techniques have been used to preserve plants in the past. The traditional method, Disease identification by the automated procedure is beneficial as it reduces the unnecessary job of monitoring large farms of plants, and it identifies disease signs at a very early stage, after they appear on plant leaves [12].

Plant pathologies are observed in several ways. The symptoms in some of these diseases are not visible, therefore it becomes evident too late to act, requiring a detailed analysis. However, because most diseases exist in the visible range, professional trainers with the naked-eye examination are the most common method for detecting plant diseases in practice [13]. With the advancement of computer vision, machine learning, computer vision, and artificial intelligence technologies, there is an advancement is in implementing innovative models that allow effective and timely diagnosis of plant leaf disease. Machine learning has risen in popularity among big data technology and high performance computing to introduce new possibilities for unraveling, measuring, and understanding data-intensive systems of agricultural operations [14].

ML is known as a scientific area that allows machines to learn without being explicitly programmed. For plant disease detection, several researchers have developed automated detection and identification algorithms. Also, Artificial neural networks (ANNs) and Support Vector Machines (SVMs) are two techniques for identifying plant diseases currently being used. They are integrated with various image preprocessing approaches to enhance feature extraction. Singh et al. (2019) , used machine learning, artificial intelligence, and computer vision to create an automated model for identifying plant leaf diseases [15], [4].

To detect diseaseson agricultural products machine learning, classification based methods, and image recognition approaches have been used. Regardless of the process, correctly classifying a disease as it initially appears can be a critical stage in effective disease control[16]. This day, everybody has a cell phone. As a result, he created an Android program. The program identifies the concern in the leaf tissue. This software has a higher resolution to view [17].

The author used a machine learning algorithm to analyze 87K data images which is categorized into 38 different classes. They want 11 different types of farming plants. They achieve an average precision of 85.53 percent to 99.34 percent [18]. Numerous computer vision methods, supported by various classification procedures, were used in disease detection techniques. One of the research fields of machine and agriculture is detecting disease from plant pictures . With the significant development of computer vision, this technology has been applied in agricultural robotics, and it continues to play an important role in its growth [19].

Agricultural automation technology based on computer vision is frequently used in agriculture to increase production and sustainability. Smart applications based on computer vision algorithms are becoming a standard part of agricultural production management [20]. To enhance disease recognition accuracy, significant work has been done using various methods and techniques of machine learning algorithms.

Plant diseases can demonstrate symptoms and signs in different parts of the plant, including the leaves, stems, fruits/seeds, and so on. This is feasible due to new digital technology that consistently tracks the natural universe and produces large amounts of data at an increasing rate [21],[5],[56]. Thus, Smart farming is essential for resolving food production's efficiency, ecological consequences, food security, and environmental consequences. Sustainable agriculture is a vital component of smart farming as it improves the environmental protection and resource based on which agriculture relies while still meeting basic human nutritional demands.

Detect UPI Fraud By Using Machine learning[50]. Ethical hacking has emerged as a crucial practice, enabling organizations to fortify their defenses and safeguard their assets[51].

II. LITERATURE REVIEW

Early detection of plant diseases is one of the most important practices in agriculture [21] . Identifying leaf diseases early is crucial for maintaining plant health and ensuring high-quality crops [22]. With the large variety of diseases affecting plants, it's become increasingly difficult to control plant quality in agriculture [23]. Most of the research so far has focused on using image recognition and computer vision techniques to create systems that can detect plant diseases by analyzing images of leaves.

Currently, many of these diagnoses are made manually, which can be slow and inaccurate, making it difficult to pinpoint the exact nature of the disease. This has highlighted the need for automated systems that can quickly and accurately detect diseases [24] . As a result, researchers have been working on developing technologies that can improve disease detection. In the paper, the authors describe a method for classifying and detecting plant leaf diseases, showing how their system works to identify and categorize different plant diseases based on leaf images [25].

Pre-processing is performed before extracting features in this case.In the similar paper , several steps in the identification of unhealthy plant leaves need RGB image accession [26]. The input image is translated from BGR to RGB format.OpenCV reads images in the BGR colour space, which means the pixel values are arranged in the order of Blue, Green, and Red. However, many image processing tasks, especially those in other libraries like PIL (Pillow) or when displaying images with libraries like Matplotlib, expect the colour format to be in RGB (Red, Green, Blue) [27]. Computer vision is increasingly being used to identify plant diseases in a variety of ways. Perhaps one them, as described by the authors in paper , is disease detection by extracting colour features [28].

The result indicate that disease spots were successfully observed and were unaffected by noise from various causes, including camera interference [29]. Furthermore, the detection of plant disease has been studied by implementing an experiment on various plant.They developed a software model that can be used to predict disease methods for agricultural crops [30]. In addition, the author of this article examines the identification and classification of deviation in plants for training and research purposes, using corn leaves as an example [31]. In this article author examines the total accuracy of training set is 0.9816 and loss is 0.0576 and the accuracy of validation set is 0.9606 and loss is 0.1325 In order to identify the species of leaf, pest, or disease, some methods use feed-forward neural networks of machine learning [32],[3],[2].

III. PROPOSED METHODOLOGY

A. Dataset Description

For classification purpose we need a dataset to use and, in this research, we used the New Plant Diseases Dataset which contains 64996 photos of both healthy and unhealthy leaves 19 different plan species which has been captured in different environments. These images have been classified into two different classes healthy and diseased class. These images are of Thirteen different plants are Apple, Blueberry, Cherry, Corn, Grape, Orange, Peach, Pepper Bell, Potato, Rasberry, Soyabean, Strawberry, Tomato. Sample leaf images from New Plant Diseases Dataset is presented in fig. A brief description of dataset is given in table 1:

Table 1. Plant Diseases Dataset

Class	Plant Diseases	Images
Apple	Scab	2016
	Black rot	1987
	Cedar Apple_rust	1760
	Healthy	2008
Blueberry	Healthy	1816
Cherry	Healthy	1926
	Powedery_mildew	1683
	Common_rust	1907
Corn		
	Healthy	1859
	Northern_leaf_Blight	1908
	Cercospora_leaf_spotgra	1642
Grape	Black_rot	1888
	Esca	1920
	Healthy	1692
	Leaf_Blight	1722
Orange	Huanglongbing	2010
Peach	Bacterial_spot	1838
	Healthy	1728
Pepperbell	Bacterial spot	1913
	Healthy	1988
Potato	Healthy	1824
	Late_Blight	1939
	Early_Blight	1939
Rasberry	Healthy	1781
Soyabean	Healthy	2022
Straberry	Healthy	1824
	Leaf scorch	1774
	Healthy	1926

Tomato		
	Early_blight	1920
	Late_blight	1851
	Leaf_mold	1882
	Septoria Leaf_spot	1745
	Spider_mites_two_spoted	1741
	Mosaic_virus	1790
	Target_spot	1827
	Yellow_leaf_curl_virus	1961


(a) Apple- scab


(b) Blueberry-healthy


(C) Corn-common rust


(d) Grape-black rot


(e) Peach-healthy


(f) Potato-late blight


(g) Soyabean-healthy

(h) Strawberry-leaf scorch

(i) Tomato-leaf mold

Figure 1. Sample Leaf Images from Dataset

B. Methodology

a. Convolution Neural Network

Convolutional Neural Network (CNN) is the extended version of artificial neural networks (ANN) which is predominantly used to extract the feature from the grid-like matrix dataset. For example visual datasets like images or videos where data patterns play an extensive role. Convolutional Neural Network consists of multiple layers like the input layer, Convolutional layer, Pooling layer, and fully connected layers. The Convolutional layer applies filters to the input image to extract features, the Pooling layer down samples the image to reduce computation, and the fully connected layer makes the final prediction. The network learns the optimal filters through backpropagation and gradient descent.

i). Mathematical Overview of Convolution

Now let's talk about a bit of mathematics that is involved in the whole convolution process.

• Convolution layers consist of a set of learnable filters (or kernels) having small widths and heights and the same depth as that of input volume (3 if the input layer is image input).

- For example, if we have to run convolution on an image with dimensions 34x34x3. The possible size of filters can be axax3, where 'a' can be anything like 3, 5, or 7 but smaller as compared to the image dimension.
- During the forward pass, we slide each filter across the whole input volume step by step where each step is called stride (which can have a value of 2, 3, or even 4 for high-dimensional images) and compute the dot product between the kernel weights and patch from input volume.
- As we slide our filters we'll get a 2-D output for each filter and we'll stack them together as a result, we'll get output volume having a depth equal to the number of filters. The network will learn all the filters.

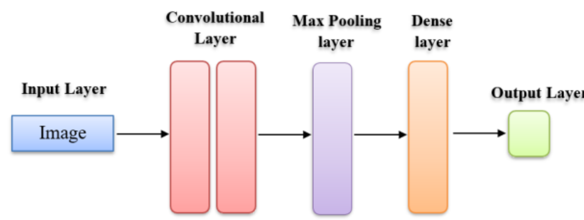

Figure 2. Simple Architecture of CNN

ii). Layers Used to Build ConvNets

A complete Convolution Neural Networks architecture is also known as covnets. A covnets is a sequence of layers, and every layer transforms one volume to another through a differentiable function. Types of Layers: Datasets

Let's take an example by running a covnets on of image of dimension 32 x 32 x 3.

- Input Layers: It's the layer in which we give input to our model. In CNN, Generally, the input will be an image or a sequence of images. This layer holds the raw input of the image with width 32, height 32, and depth 3.
- Convolutional Layers: This is the layer, which is used to extract the feature from the input dataset. It applies a set of learnable filters known as the kernels to the input images. The filters/kernels are smaller matrices usually 2×2, 3×3, or 5×5 shape. it slides over

the input image data and computes the dot product between kernel weight and the corresponding input image patch. The output of this layer is referred as feature maps. Suppose we use a total of 12 filters for this layer we'll get an output volume of dimension 32 x 32 x 12. By adding an activation function to the output of the preceding layer, activation layers add nonlinearity to the network. it will apply an element-wise activation function to the output of the convolution layer. Some common activation functions are RELU: max(0, x), Tanh, Leaky RELU, etc. The volume remains unchanged hence output volume will have dimensions 32 x 32 x 12.

- Pooling layer: This layer is periodically inserted in the covnets and its main function is to reduce the size of volume which makes the computation fast reduces memory and also prevents overfitting. Two common types of pooling layers are max pooling and average pooling. If we use a max pool with 2 x 2 filters and stride 2, the resultant volume will be of dimension 16x16x12.
- Flattening: The resulting feature maps are flattened into a one-dimensional vector after the convolution and pooling layers so they can be passed into a completely linked layer for categorization or regression.

C. System Architecture

Performance evaluation metrics and methods are crucial components in the development and evaluation of plant disease. These metrics and methods provide insight into the performance of the model and enable researchers and practitioners to compare different models and techniques. The image shows a confusion matrix, which is a key concept in evaluating the performance of a classification model. The confusion matrix consists of four main components:

- True Positive (TP): The model correctly identifies a positive instance.
- False Positive (FP) (Type I Error): The model incorrectly classifies a negative instance as positive.
- False Negative (FN) (Type II Error): The model incorrectly classifies a positive instance as negative.
- True Negative (TN): The model correctly identifies a negative instance.

a. Performance Metrics

Using these values, we calculate three important metrics: Precision, Recall, and Accuracy.

i). Precision (Positive Predictive Value)

Precision is the proportion of true positives among the total number of positive predictions made by the model. It is calculated by dividing the number of true positives by the sum of true positives and false positives. High precision means fewer false positives.

$$\text{Precision} = \frac{\sum TP}{\sum TP+FP} \qquad \text{(I)}$$

ii). Recall (Sensitivity or True Positive Rate)

Recall is the proportion of true positives among the total number of actual positive cases. It is calculated by dividing the number of true positives by the sum of true positives and false negatives. High recall means fewer false negatives.

$$\text{Recall} = \frac{\sum TP}{\sum TP+FN} \qquad \text{(II)}$$

iii). Accuracy

Accuracy is the proportion of correct predictions made by the model. It is calculated by dividing the number of correct predictions by the total number of predictions made by the model. It is useful when the dataset is balanced, but can be misleading in imbalanced datasets.

$$\text{Accuracy} = \frac{\sum TP+TN}{\sum TP+FP+FN+TN} \qquad \text{(III)}$$

b. Practical Interpretation

A high precision but low recall means the model is conservative, making fewer errors in positive predictions but missing many real positives. A high recall but low precision means the model captures most positives but also includes many false positives. Balanced precision and recall are needed for a well-performing model.

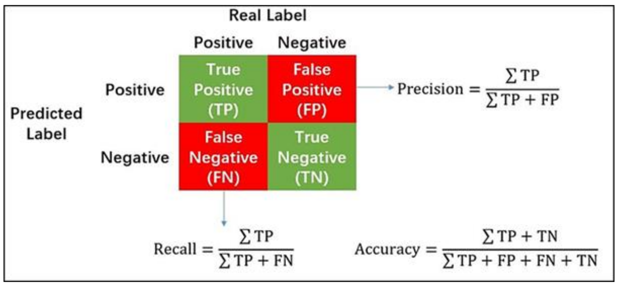

Figure 3. Confusion Matrix

D. Algorithm Description

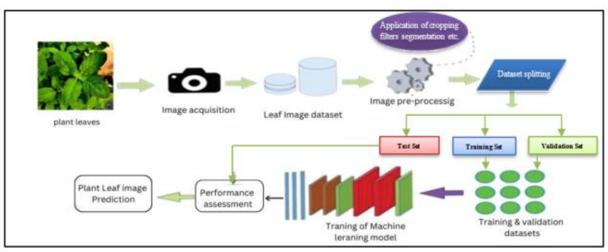

Figure 4. Plant Leaf Image Prediction Process

This algorithm represents a machine learning-based plant leaf image prediction process. It outlines the steps involved in acquiring, processing, and utilizing various plant images to train a machine learning model.

- Plant Leaves: The process begins with capturing images of plant leaves in a dataset.
- Image Acquisition: A camera or imaging device is used to collect images of plant leaves, creating a dataset.
- Leaf Image Dataset: The acquired images are already stored in a database for further processing.
- Image Pre-Processing: Various techniques, such as filtering, and segmentation, are applied to image quality and extract useful features.
- Dataset Splitting: The dataset is divided into three subsets:

- Training Set: Used to train the machine learning model.
- Validation Set: Used to tune the model parameters and prevent overfitting.
- Test Set: Used to evaluate the model's performance after training.

    - **Machine Learning Model Training:**

- The pre-processed and split dataset is fed into a machine learning model.
- The model learns patterns and features from the training and validation datasets.

    - Performance Assessment: The trained model is evaluated using test data to measure accuracy, precision, recall, and other metrics.

    - Plant Leaf Image Prediction: The final trained model is used to classify plant leaves based on the learned features, which can help in detecting diseases or identifying plant species.

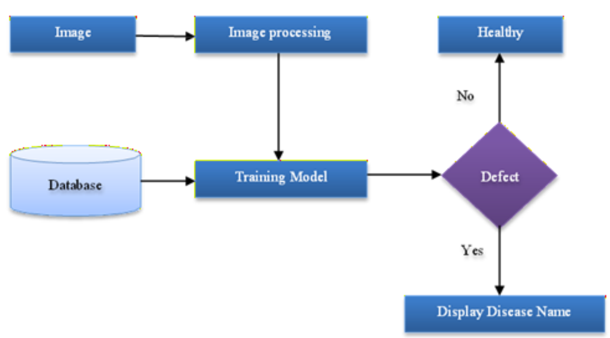

Figure 5. Block Diagram of Plant Leaf Diseases Prediction

IV. RESULTS

A. Accuracy and Loss of Training Set

```
train_loss,train_acc=model.evaluate(training_set)
2197/2197 ━━━━━━━━━━━━━━━━━━━━ 1455s 662ms/step - accuracy: 0.9816 - loss: 0.0576
train_loss, train_acc = model.evaluate(x_train, y_train) print(f"Training Loss: {train_loss}, Training Accuracy: {train_acc}")
print(train_loss,train_acc)
0.053890153765678406 0.9833700656890869
```

B. Accuracy and Loss of Validation Set

```
epochs=[i  for i in range(1,11)]
plt.plot(epochs,training_history.history['accuracy'],color='red',label='Training Accuracy')
plt.plot(epochs,training_history.history['val_accuracy'],color='blue',label='validation Accuracy')
plt.xlabel("no. of epoches")
plt.ylabel("Accuracy result")
plt.title("Visulization of accuracy")
plt.legend()
plt.show()
```

C. Visualization of Accuracy

D. Visualization Single Image of Test Set

```
import cv2
image_path="test/test/CornCommonRust3.JPG"
#reading Image
img=cv2.imread(image_path)
img=cv2.cvtColor(img,cv2.COLOR_BGR2RGB)


plt.imshow(img)

plt.title("Test Image")
plt.xticks([])
plt.yticks([])
plt.show()
```

E. Testing of Model

```
model_prediction=class_name[result_index]
plt.imshow(img)
plt.title(f"Disease Name:{model_prediction}")
plt.xticks([])
plt.yticks([])
plt.show()
```

F. Prediction of Model

```
model_prediction
'Corn_(maize)___Common_rust_'
```

V. DISCUSSION

The future scope of plant disease prediction using machine learning (ML) is vast and highly promising. With the rapid advancement of AI, data science, and remote sensing technologies, the application of machine learning in agriculture is expected to grow significantly. Here are several areas where machine learning can have a transformative impact on plant disease prediction:

A. Improved Disease Diagnosis and Prediction Models

- Real-Time Detection: ML algorithms can analyze data from sensors, images, and environmental factors (temperature, humidity, soil moisture) to detect plant diseases in real-time. This would allow for early detection, even before symptoms are visible, enabling proactive management.

- Enhanced Accuracy: By using deep learning and neural networks, models can improve accuracy in disease diagnosis, even when the symptoms are subtle or similar to other diseases. This would reduce human error and misidentification.

B. Integration with IoT and Remote Sensing

- Precision Agriculture: The use of Internet of Things (IoT) devices combined with ML can enable continuous monitoring of plant health. Drones, satellites, and ground sensors can capture data about the crops, which can be analyzed by ML algorithms to detect early signs of diseases.

• Satellite and Drone Imaging: With advances in drone technology and satellite imagery, ML models can analyze vast amounts of visual data to identify early symptoms of diseases like blight, rust, or mildew. This can help farmers manage large fields efficiently.

C. Predictive Analytics and Risk Assessment

• Climate Modeling: ML can help analyze weather patterns and environmental conditions to predict when and where plant diseases are most likely to occur. By combining climate data with historical disease data, predictive models can provide farmers with forecasts of disease outbreaks.
• Risk Mapping: Using spatial data and ML, disease risk maps can be created, allowing farmers to understand where their crops are most vulnerable. This would enable them to take targeted preventive measures in high-risk areas, improving overall crop health and yield.

D. Disease Resistance and Breeding Programs

• Accelerated Breeding: Machine learning models can analyze genetic data to predict how certain plant varieties will respond to specific diseases. This can speed up the process of developing disease-resistant crops by identifying desirable traits for breeding.

• Genetic Data Analysis: ML algorithms can identify genetic markers associated with disease resistance, aiding the development of genetically modified or naturally resistant plants.

E. Automated Solutions for Disease Control

• Robotics and Autonomous Systems: ML can also play a key role in automating the treatment of plant diseases. Robots equipped with machine vision systems can identify infected plants and apply the correct treatment (e.g., pesticides, fertilizers) precisely, minimizing the use of chemicals and reducing labor costs.

• AI-Powered Sprayers: Autonomous sprayers guided by AI can detect plant diseases through images and apply targeted doses of chemicals, reducing waste and environmental impact.

F. Integration with Mobile Apps

• User-Friendly Tools: Mobile apps that use ML-based disease prediction can allow farmers to easily identify plant diseases by simply taking pictures of their crops. These apps can provide farmers with real-time advice and treatment recommendations, which is especially useful in developing regions.

• Crowdsourced Data: Mobile apps can collect disease data from farmers worldwide, feeding into global ML models that improve the prediction and detection of plant diseases on a larger scale.

G. Data-Driven Pest Management

• Pest-Disease Interactions: ML models can not only predict plant diseases but also help in managing pest-related issues. Many pests, like aphids or beetles, spread diseases, and understanding the relationship between pests and diseases can lead to more effective pest management strategies.

H. Sustainability and Eco-Friendly Solutions

• Reduced Chemical Use: By using ML for early disease detection, the need for widespread pesticide application can be reduced. This contributes to more sustainable farming practices, reduces the risk of pesticide resistance, and helps maintain soil and environmental health.

• Integrated Pest Management (IPM): ML can help farmers move towards Integrated Pest Management strategies, where diseases and pests are controlled using a combination of biological, cultural, and chemical methods, based on data-driven insights.

VI. CONCLUSION

We have attempted to apply a solution for the problem of plant disease detection in this specific paper. Our study uses photos of plant leaves to identify ailments, which reduces costs and increases profits in the agriculture industry, is a powerful addition to current systems. In addition to plant disease detection, a cure that aids farmers in controlling the illness and minimising production loss. If properly applied, this technology offers a lot of promise for both household and agricultural application. With the help of this model, we can quickly detect plant diseases, reducing crop damage and enhancing food security. This creative method increases productivity and yields precise outcomes

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