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Machine Learning Approach For Image Based Crop Disease Detection

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ABSTRACT : One of the essential commodities for life, food is necessary for everyone to survive. However, not everyone has the right to a satisfying lunch each day. According to estimates from the World Health Organization, two-thirds of people worldwide are food insecure. Smart agriculture is the technologically sophisticated solution to this long-standing issue, helping to increase farmland yield while using the fewest resources possible. Although crop diseases pose a major threat to food security, it is still difficult to identify them quickly since many regions of the world lack the necessary infrastructure. Impressive progress has been made in the area of leaf-based picture categorization since the development of accurate approaches. The suggested system operates in two steps, the first of which is training data sets. To do this, training sets with both healthy and unhealthy data must be used. The second stage entails crop monitoring and disease detection using the CNN technique, which contains several implementation processes such as data set construction, extracting features, classifier training, and classification. In order to classify the photos of damaged and healthy leaves, CNN has been simultaneously training on data sets of both diseased and healthy leaves. Overall, we can detect plant diseases on a broad scale by employing machine learning to train massive, publicly accessible data sets.

KEYWORDS : Agriculture, CNN, Diseased and Healthy leaf, Segmentation, Classification, Neural Network, Image Preprocessing, Feature Extraction, ML.

1.INTRODUCTION

Amazing progress has been made throughout human history to increase agricultural output while using fewer labor and resources. However, a long-term match between supply and demand has been thwarted by the rapid population expansion. According to projections, there will be 9.8 billion people on the planet by 2050, a roughly 25% increase. Since everyone needs food to survive, it is one of life's most important resources. However, not everyone has the right to a sumptuous dinner. Food is a basic resource for life since it is necessary for everyone to have access to it. But not everyone is entitled to a sumptuous meal every day. Two thirds of the world's population suffers from undernutrition, according to the World Health Organization. A state-of-the-art approach to this perennial problem, smart agriculture maximizes farmland productivity while consuming the fewest resources possible. Thanks to recent developments in information and communication technology, a robust ACPS has been created. The loss of crops as a result of various diseases must be taken into account while focusing on boosting food production.

Farmers can detect crop diseases with the aid of the prediction of crop diseases tool. In India, farmers are always concerned about the diagnosis. Monitoring and management tactics will be more successful if diseases are detected early. Convincing the farmer to apply a limited quantity of pesticide to a specific area where an infection may exist or where a disease outbreak may occur in the future is the aim of this project.

2.LITERATURE REVIEW

According to Agrocares et al. [1], a plant's status, crop output, and quality are all significantly influenced by its ability to develop healthily. Traditional crop analysis techniques usually rely on estimation and farmer intuition to ascertain the proper growth and development. The network technology utilized in IoT-based agriculture, including the network architecture and layers, topologies, and protocols, has been thoroughly reviewed by A. Berenguer et al. [2]. A. Gupta et al. [3] anticipate that by mid-2030, there will be 8.6 billion people on the planet due to the exponential growth in the human population. Crop diseases that harm agricultural products while they are growing pose the biggest threat to food security. D.A. Bashish et al. [4] Ubiquitous computing has been proposed as a computational paradigm that enhances the utilization of computing equipment by enabling users to use them whenever and wherever they are needed. From an energy perspective, it is often essential to finish the entire UbiComp task in a predetermined amount of time while consuming the least amount of energy. According to J. Lowenberg-DeBoer et al. [5], the design and functioning of smart cities that employ them encounter conflicting issues with energy consumption and security. Powering Internet of Things devices like sensors and their communication is a challenge because batteries have a limited lifespan and need costly, risky maintenance and disposal. Contrary to common assumption, the agriculture industry has become more data-driven, accurate, and sophisticated than ever before, according to M. Ayaz et al. [6]. The quick development of Internet of Things (IoT)-based technologies has fundamentally altered nearly every industry, including "smart agriculture," which moved from statistical to quantitative approaches. Rechargeable Wireless Sensor Networks were introduced by Peng Jiang et al. [7], where nodes are powered by solar energy and radio frequency signals from nearby nodes. Both the link capacity, which is impacted by the group of transmitting nodes, and the energy available at the sensor nodes have an impact on this rate. According to R. Beulah et al. [8], deep neural networks have proven effective across numerous industries. But a lot of DNN models are large and deep, which means they need a lot of energy and storage during the training and inference stages. A multi-level compression strategy was proposed by them. The suggested compression approach uses cross-layer parameter-reducing techniques like structure compression, weight compression, and representation compression to allow for order-of-magnitude reductions in network dimensions for both training and inference with negligible accuracy loss. As a result, DNN models have extremely high accuracy and efficiency. According to S. Saraswat et al. [9], the internet of things expands the scope of intelligent agriculture and farming. WiFi-based long distance networks and fog computing can be used to efficiently connect farms and agriculture bases in remote locations. Shekha, S., and others [10] It takes a lot of effort and time to keep a close watch on illness on the farm. We can more effectively identify plant diseases by utilizing AI and the internet of things. Without the use of images, researchers have created techniques that use AI and IoT to identify plant diseases. To acquire the images or data for hyperspectral investigation, manual labor is required.

3.PROPOSED METHODOLOGY

The proposed approach aims to modernize India's farming practices and provide farmers more authority to increase crop yields and profits. The system identifies crop diseases, provides farmers with all the data they need on such diseases, and tries to help them select crops that are best suited for production. Farmers will have more control for their livelihoods as a result of increased crop productivity and quality. The system primarily uses content-based filtering algorithms and convolutional neural networks to help farmers by identifying diseases and suggesting crops. A dataset that is characterized by the selected weather condition and geographical parameter is analyzed and processed for the crop recommendation system.

Additionally, crop illness is identified by image classification using CNN, a Machine Learning system. The training data comprises 38 distinct disease kinds, and the 14 crops are separated into the categories of fruits, vegetables, and fruit vegetables for disease detection. A cure is shown when a disease has been detected. Convolutional neural networks (CNN) are used to identify diseases and recommend crops to farmers, as seen in Figure 1. A dataset that is differentiated by the geographic parameter and weather conditions it has selected is subjected to an analysis and processing phase for the crop recommendation system. Convolutional Neural Networks (CNN), a component of the Deep Learning Algorithm, are also used in crop disease diagnosis. The training data for disease detection includes 38 distinct sickness kinds, and the 14 crops are separated into the categories of fruits, vegetables, and fruit vegetables. Following the identification of an illness, a cure is presented.

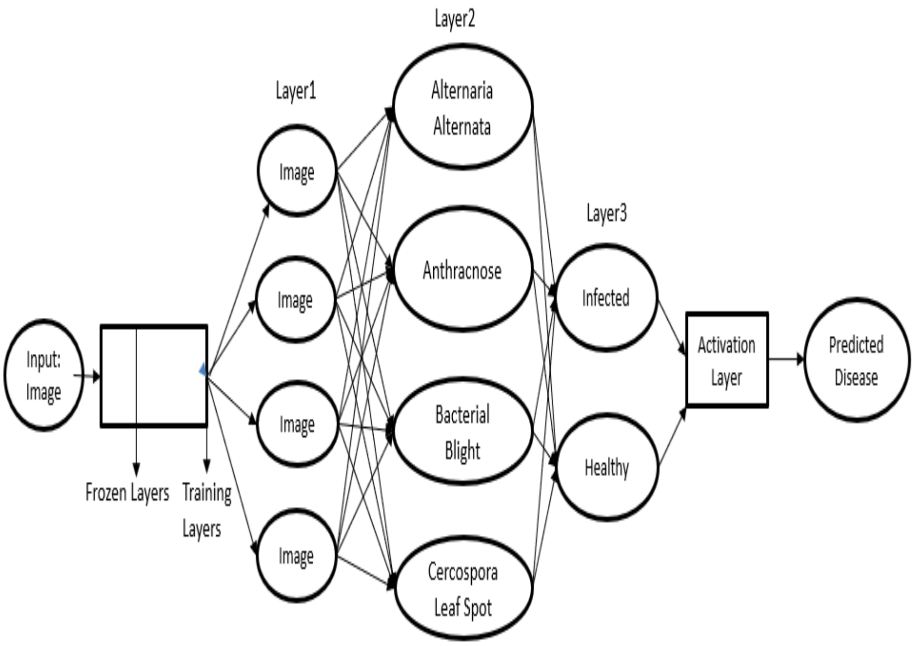

Figure 1: Crop Disease Prediction Architecture

3.1 Data Flow Diagram : As seen in Figure 2, the flow technique will determine the coding scheme for the categorization. The data set is used to collect the information. Any missing values are eliminated during the preparation of the gathered data. Since machine learning can only comprehend 0s and 1s, each of the categories have been transformed into numerical columns. Following feature extraction, training data photos are used to train the model. The model is then trained using the CNN technique to determine whether a leaf has an infection or not; if it is, the proportion of the affected area is displayed.

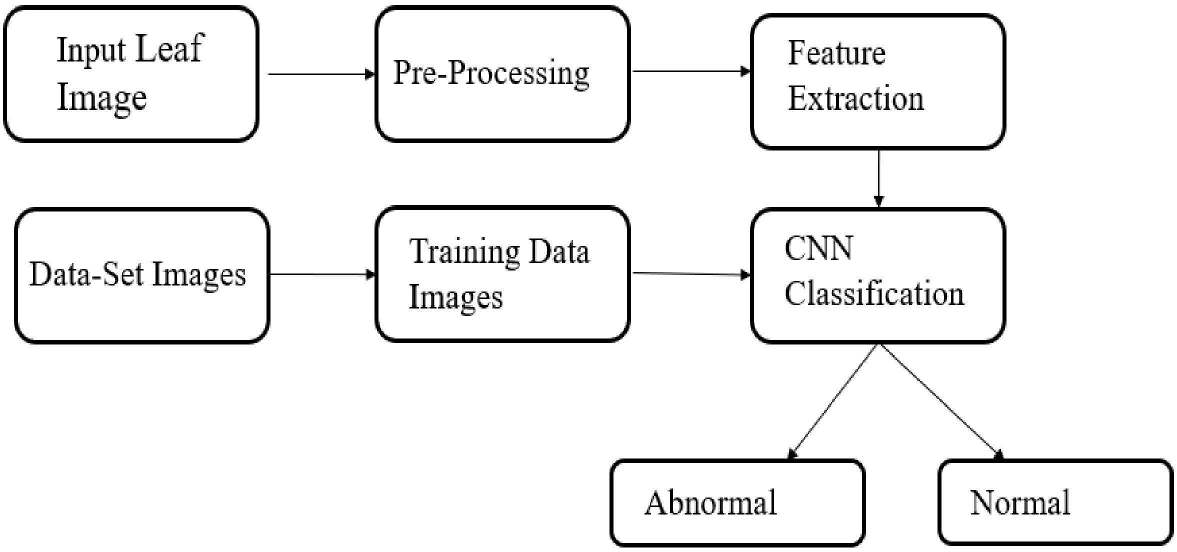

Figure 2: Crop Disease Prediction Data Flow

3.2 Sequence Diagram : The sequence diagram, sometimes referred to as an event diagram, is shown in Figure 3 and shows how messages move through the system. Users, data storage, and CNN's algorithm are all included in the sequence diagram that is shown there. Prior to creating test and training data sets, the collected data must be stored in data storage. The characteristics are then eliminated. The CNN technique is used to train the model prior to verification. Once the leaf image has been loaded, the result is produced.

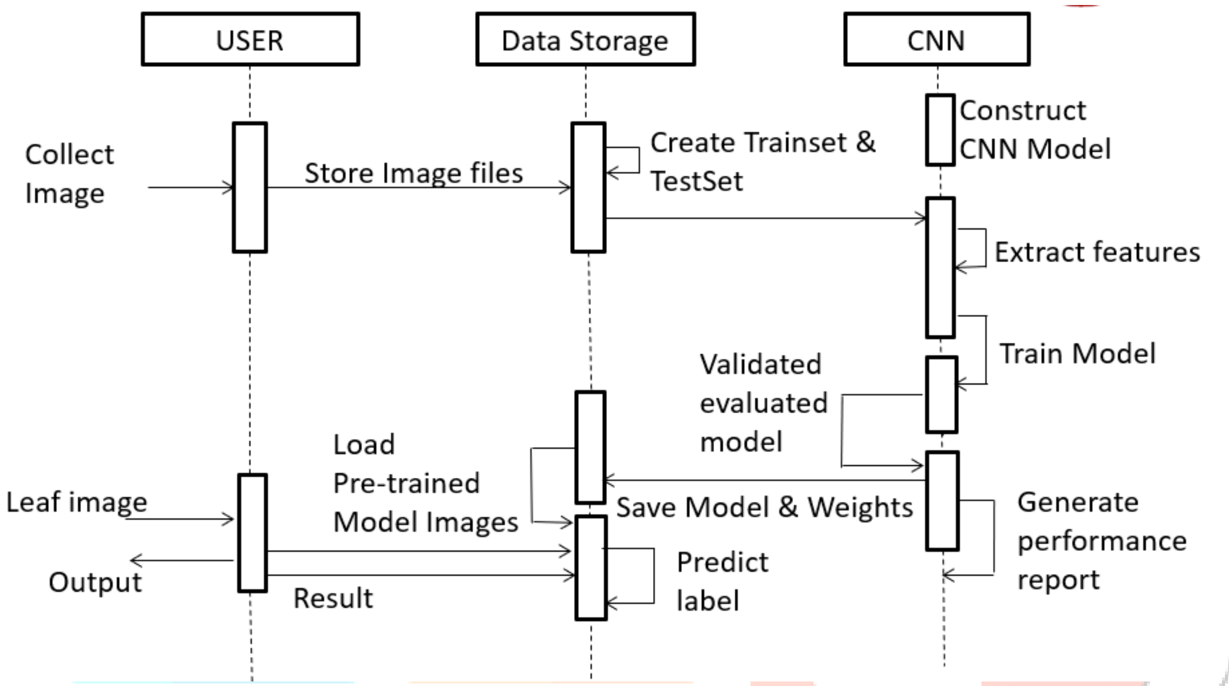

Figure 3: The Model Building Sequence

3.3 Convolutional Neural Networks Algorithm : The organization of feed-forward artificial neural networks, often known as CNNs or Convents, is modeled after the structure of the visual cortex in animals. Convolutional neural networks (CNNs) can learn intricate objects and patterns because of its input layer, output layer, a number of hidden layers, and numerous parameters. Prior to applying an activation function, the input is subsampled using pooling and convolution techniques. All of the hidden layers are originally only partially connected, with the output layer being the final layer to be fully connected. The size of the input image is mirrored in the output form. The technique of combining two functions to create the output of a third function is called convolution. A feature map is produced once CNNs have processed a difficult input image. The weights and biases in filters are network vectors that were created at random. The weights and biases used by CNN are the same for every neuron, not unique to each one of them. Each of the several filters that can be made removes a unique property from the input. Filters are also referred to as kernels.

4. MODEL PROCESSING WORKFLOW

4.1 Analysis of input images Making use of pre-processing : We suppressed undesirable distortions in order to enhance a number of features that are crucial for the application that we are developing. Different applications may have different characteristics. To achieve accurate results, we magnified the leaf's most severely damaged area. The basic building block of digital images are pixels, which are tiny boxes that show the color and brightness values for that particular portion of the image. To achieve the intended effects for the image, image processing comprises modifying these pixels in a preset manner.

4.2 Image segmentation Process Using image segmentation : Initially, the digital image was divided into several image segments, sometimes referred to as image components (sets of pixels) or image regions. The objective is to make an image representation more relevant and consumable by either simplifying it or changing it. To locate objects and boundaries (such as lines, curves, etc.) in photos, image segmentation was employed. Image segmentation is the process of assigning a label to each pixel in a picture so that pixels with the same label have specific characteristics. The digital image was first separated into a number of image segments, also known as image regions or image components (sets of pixels). The goal is to either simplify or alter an image representation in order to make it more relevant and digestible. Image segmentation was used to identify objects and boundaries (such as lines, curves, etc.) in photographs. The technique of giving each pixel in an image a label so that pixels with the same label have particular traits is known as image segmentation.

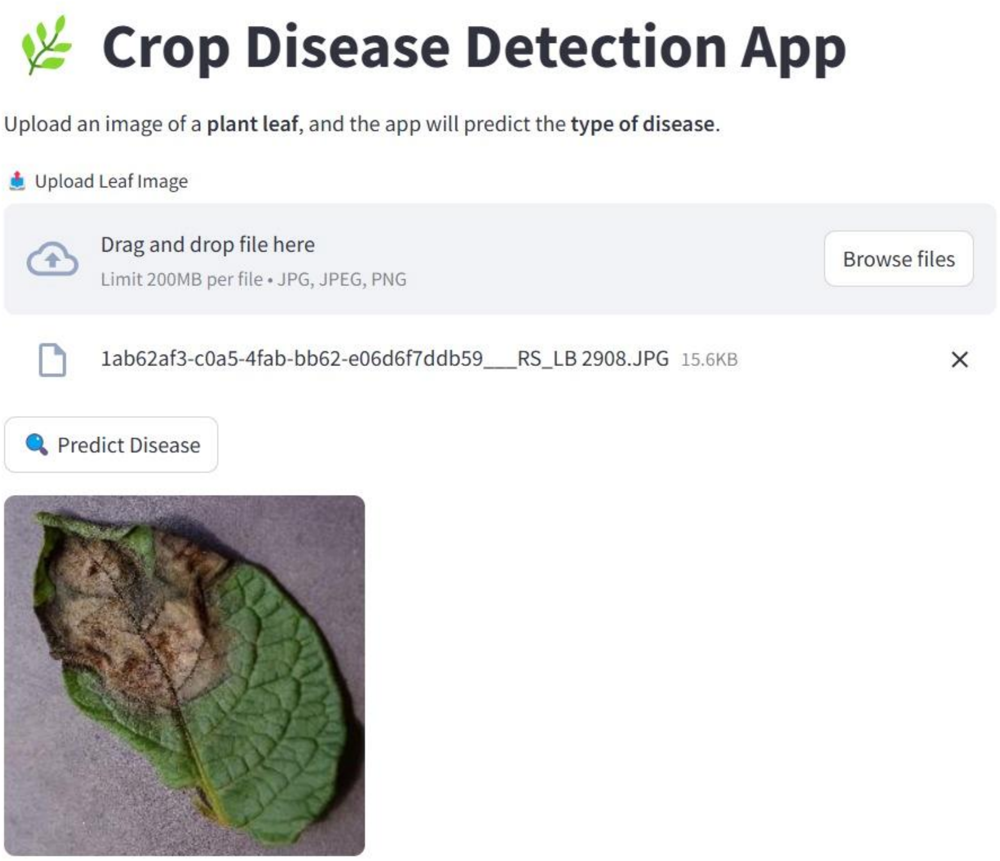

Figure 4: Image Processing and Normalization

Model predicts whether or not the leaf is infected. To make it easier to view, the test image is first loaded and then reduced in size. The figure 4 shows the processed and segmented image. Figure 5 displays the user interface for a system that uses test leaf photos as input parameters to predict crop diseases. To ascertain whether or not the test leaf is infected, the system makes use of the input parameters

The disease of the crop is displayed on the uploaded test image as shown as follows

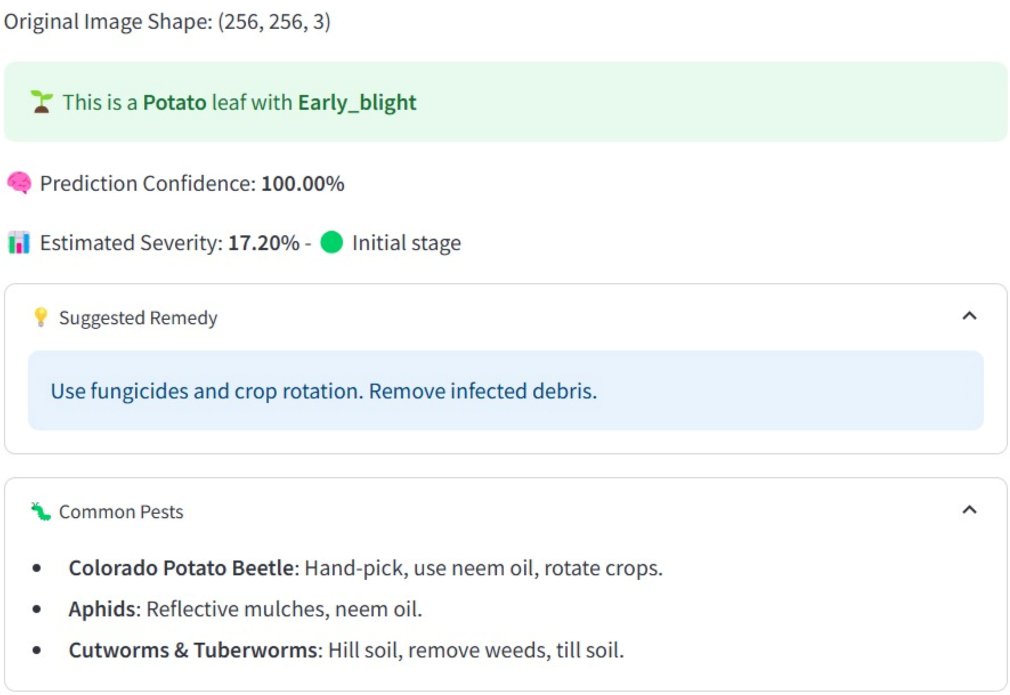

Figure 5 : Detection of crop disease

5. RESULTS AND DISCUSSIONS

Indian farmers would be able to boost agricultural yields and, eventually, their revenue with the aid of this recommended approach. Our strategy include identifying crops for cultivation with precision, recognizing agricultural illnesses, and giving farmers all the information they require to help them. Farmers will have more control over how they sustain themselves if agricultural yield and quality are increased. Our approach is centered on using CNN and content-based filtering techniques to give farmers disease diagnoses and crop recommendations. A dataset that is traditionally defined by the parameters of the chosen region and the meteorological conditions is analyzed and processed for the crop recommendation system.

Additionally, CNN uses deep learning techniques to classify the images in order to identify agricultural diseases. Using 38 various kinds of disease training data, 14 distinct crops that are categorized as "vegetables, fruits, and fruit vegetables" need to be examined for the presence of disease. Once the illness has been identified, the best course of action is first decided.

The model's performance and accuracy during training and validation are illustrated in the accuracy plot shown below.

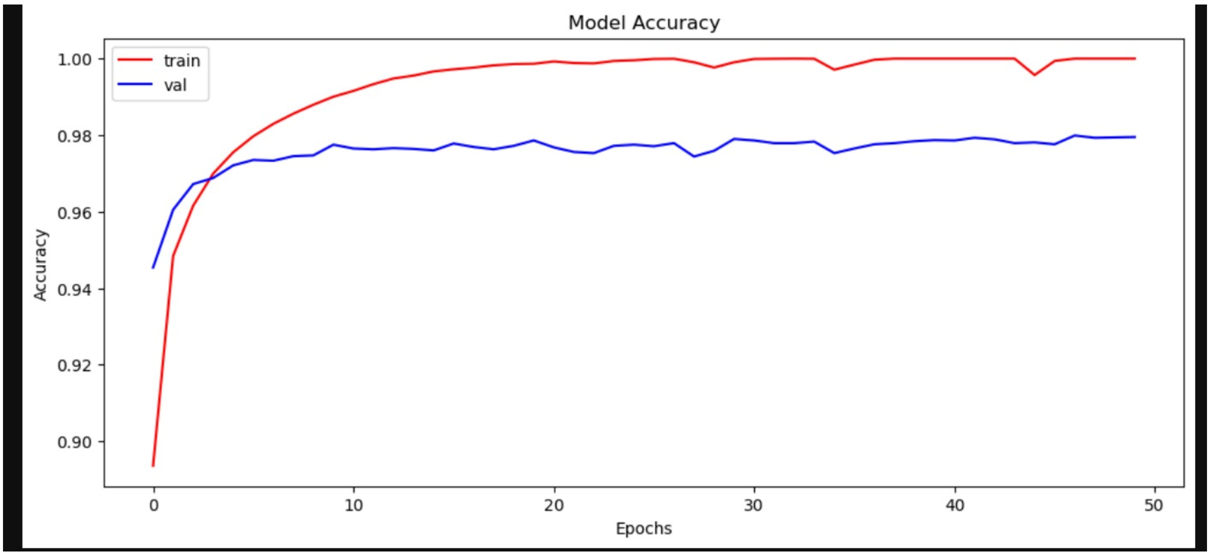

Figure 6: Training and Validation Accuracy of the CNN Model

6. CONCLUSION

In order to reduce farming uncertainty and increase output, this approach helps farmers find a solution to the issue. The input image is initially reduced for improved visual clarity before being segmented using k-means clustering for speedy and precise analysis. The segmented image is then converted to grayscale so that features can be extracted. to predict whether or not a leaf has been harmed and what proportion of the leaf has been impacted, allowing farmers to determine the extent of the damage. The results have a 98% accuracy rate. In the identification and categorization of plant leaf diseases, computer vision and deep learning algorithms perform better than previous image classification methods based on the extraction of human features.

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