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Smart Agri Disease Detection of Black Gram Plant Leaf Using the Cloud-Based Yolov8 Intelligent System.

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Abstract— Infectious diseases affecting plants can have a major negative impact on economic output. Phenotyping plants is an essential part of plant characterization for tracking plant development over time. The urdbean leaf crinkle virus (ULCV) causes crinkled leaf disease, a plant disease that mostly affects black gram (Vigna mungo), a significant pulse crop in India. Crinkled disease is devastating to crops and the agricultural economy as a whole, causing farmers to lose out on a lot of money and harvests. Plant diseases cost USD 220 billion annually, according to the FAO (Food & Agriculture Organization). The early and accurate diagnosis of a disease (ULCV) is crucial for any economy that relies on agriculture. computer vision and Image processing are among the many cutting-edge methods for detecting plant diseases early. Preprocessing images, segmenting those images, extracting features, and applying machine learning algorithms to diagnose diseases are all viable options. Grey Level Co-occurrence Matrix (GLCM) is used for feature extraction. One of the machine learning methods used for detection is YOLO, which is based on a Convolutional Neural Network (CNN). In other words, YOLO led to more reliable disease diagnosis.

Keywords-YOLOv8, Machine Learning, FAO, Cloud, Computer Vision, Convolutional Neural Network (CNN).

I. INTRODUCTION

Agriculture has a significant impact on the international economy since it provides food for people all over the world and raw materials for other businesses. In addition, agricultural exports are an essential source of cash for many nations and can contribute to the alleviation of poverty and inequality. The agricultural sector in India accounts for about 17.2% of the country's GDP (GVA). This is what the 2018 Indian Economic Survey says. Sustainable Development Goal (SDG2) is dedicated to promoting sustainable agriculture, ensuring everyone has access to safe and nutritious food, and ultimately putting an end to world hunger. Agricultural output is declining over the world due to plant and crop diseases. In some situations, plant illnesses can result in losses of up to forty percent of the crop, while in others, they can render the crop unharvestable completely. Farmers may also struggle to identify crop illnesses due to a lack of resources and diagnostic equipment in many countries. Farmers can spot plant illnesses by checking their crops. Farmers can utilize handheld gadgets or crop disease recognition software to diagnose the illness in addition to eye inspection. In order to detect and diagnose agricultural diseases rapidly and accurately, computer vision is essential [1]. The use of deep learning in computer vision and machine learning can assist farmers identify and locate agricultural illnesses. Disease detection can be automated with the help of machine learning [2], saving both time and money compared to more conventional methods. In addition to using technologies like IoT devices and drones to make disease detection in big fields less labor intensive, we can also use these tools to lessen the need for manual scouting. Acquiring images, preprocessing those images, segmenting those images, extracting features from those segments, and then classifying diseases are the main components of such approaches. Important aspects of such a procedure include image acquisition, image pruning, image segmentation, feature

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extraction, and disease categorization. This paper presents an analysis of some of the major classification techniques used in such methods. This paper examines an investigation of several of the most prominent classification strategies employed in such procedures.

Crinkled leaves are plant leaves that are puckered or crinkled due to viral or genetic mutations, environmental stress, or illness. The phenomenon causes uneven leaf edges, mottling, and deformation in numerous plant species.

The experiment is carried out for Black gram (Vigna mungo) to analyze and detect the crinkled leaf disease [3]. Dataset is collected, from the locality of krishn district of Andhra Pradesh

II. RELATED WORKS

M Sardogan et.al This study provides a CNN model and Learning Vector Quantization (LVQ) algorithm for automatic feature extraction and categorization. Experimental results show that the suggested approach detects four tomato leaf diseases. [4]

Achyut Morbekar et.al, In order to identify plant diseases, the suggested system employs a new spin on the object detection method known as YOLO. In a single assessment, a neural network can predict both the bounding boxes and the class probabilities. This significantly improves the efficiency and reliability of leaf disease detection. [5]

Vijayakumar Ponnuswamy et.al The research presented below introduces a Smart Glass that can reliably categorize binary data in real time. This wearable device, after being trained with agricultural data, can tell the difference between healthy and diseased plant leaves in real time. Many problems in agriculture, healthcare, the automobile industry, and others may be solved if researchers trained the architecture with diverse datasets.[6]

Gangadevi Ganesan et.al Conventional leaf disease models use deep structured architectures and machine learning. The YOLO classifier replaces ResNet's fully connected layer for disease recognition. Experimental analysis calculates performance metrics and classification accuracy to assess the offered method's efficiency. [7]

Md. Janibul Alam Soeb et al. The goal of this research is to use artificial intelligence to detect signs of tea leaf sickness by training the fastest single-stage object identification model, YOLOv7. The findings for YOLOv7 in terms of detection accuracy, precision, recall, mAP value, and F1-score ranged from 96.4% to 98.2%. For images of tea leaves, YOLOv7 outperforms other methods, including convolutional neural networks (CNNs), deep neural networks (DNNs), the AX-Retina Net, enhanced convolutional neural network (DCNN) models, YOLOv5, and multi-objective image segmentation. [8]

Shrey Srivastava et al. project compares SSD We compared the image processing algorithms Faster R-CNN, YOLO-v3, and SSD to determine which works fastest and most efficiently. Our findings showed that YOLO-v3 outperforms Faster R-CNN and SSD [9][10].

III. METHADOLOGY

The first stage of a plant disease detection system is image acquisition. High-resolution pictures of plants can be taken with digital cameras, scanners, or drones. To improve the leaf image's quality and eliminate the background noise, pre-processing is utilized. To divide the plant image, segmentation is performed. Image Pre-processing is done to improve the quality of the leaf image and eliminate any noise that may be present [11]. Using the segmentation technique, the image of the plant is divided into separate segments, enabling us to identify and isolate the unhealthy and healthy areas of the leaf [12].

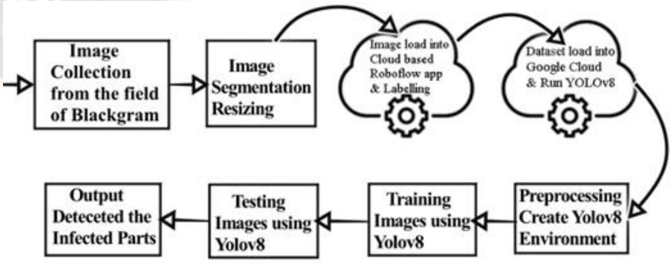

Figure-1: Flow chart for Leaf Disease Recognition.

A. *Feature Extraction*

A grey-level co-occurrence matrix (GLCM) constructed over an image represents the distribution of neighboring pixel values.[13]. GLCMs are widely employed in the study of images and other visual data as a method of texture analysis. A grey-level co-occurrence matrix (GLCM) can be used to extract the color, shape, and texture features of the sick plant portion. Different feature extraction methods, such as the gray-level co-occurrence matrix (GLCM), the spatial grey-level dependence matrix, the color co-occurrence approach, and the histogram-based feature extraction, can expand the system. Classifying textures statistically using the GLCM approach. Six color and texture features were retrieved from all of the leaf images in the collection for this investigation. Statistical texture parameters like contrast, energy, and homogeneity were extracted using the Grey Level Co-occurrence Matrix (GLCM). In addition, we compute statistical measures such as the mean, the standard deviation, and the entropy [14].

$$g_{\mathrm{i,j}} = (\mathrm{i,j})th \qquad \text{eq-1}$$

entry in GLCM

L-1 equals the number of different levels of grey. Contrast: It determines the frequency of the space. It is the difference between the highest value and the lowest value of a collection of pixels that are adjacent to each other. To provide contrast, we have:

$$\sum_i \sum_j (i-j)^2\, g_{\mathrm{ij}} \qquad \text{eq-2}$$

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Energy is a measurement that determines the textural consistency. It achieves its highest possible value when the grey level distribution maintains the same form. It is presented by

$$\sum_i \sum_j \left(g_{ij}\right)^2 \qquad \text{eq-3}$$

Homogeneity- It satisfies the value that is used in the calculation that determines how tightly the elements are distributed in the GLCM. This is provided by

$$\sum_i \sum_j \frac{1}{1+(i-j)^2 g_{ij}} \qquad \text{eq-4}$$

Mean is formulated as

$$\sum_{i=0}^{L-1} g\,(i) P\big(g(i)\big) \qquad \text{eq-5}$$

This is the standard deviation

$$\sqrt{\sum_{i=0}^{L-1} (g(i) - M)^2\, P\big(g(i)\big)} \qquad \text{eq-6}$$

Entropy measures the disorder or complexity in the image. It is large when the image is not texturally uniform and GLCM features have very small values. Entropy is given by

$$\sum_{i=0} P\,\big(g(i)\big) \log_2 P\big(g(i)\big) \qquad \text{eq-7}$$

B. Convolutional Neural Network (CNN):

CNN means Convolutional Neural Network in computer vision and deep learning. CNNs excel at picture recognition and processing [15]. It processes visual information hierarchically and locally like the human visual system. CNNs have numerous layers of neurons that conduct convolution, pooling, and activation, learning more sophisticated and abstract features from the input image. CNNs produce classification or segmentation maps that identify objects or regions of interest in input images. One aspect of object detection is classifying the various detected items. Recognizing and organizing objects can be challenging, but deep learning has significantly improved object detection. Various methods and tools were utilized to achieve this: R-CNN, Fast-RCNN, Faster-RCNN, YOLO, SSD, etc. This research focuses on "You Only Look Once" (YOLO) as a type of Convolutional Neural Network using Cloud Service [16]. Results will be accurate and timely when tested. So, we analysed YOLOv8's work by using Yolov8 to detect both image and video objects [17]. The absence of anchors in YOLOv8 reduces the number of box predictions and accelerates the non-maximum impression (NMS). YOLOv8 also employs mosaic augmentation during training. It includes the layers:

Input Layer: The input layer of a neural network relies on artificial input neurons, which are based on Input RGB Images.

Pooling Layer: The MaxPooling 2D layer has three properties: Pool Size, Strides, and Padding. Pool Size determines the window size (specified as integers or tuples of three integers) over which the maximum value is determined. For example, a Pool Size of (3,3) means the highest value within a 3x3 pooling window is selected. Strides refer to how the window moves and can be specified as an integer, a pair of integers, or None. The default Strides value is (2,2), and the Padding is (0,0,0,0).

Fully Connected Layer: The input size of this layer is set to "auto" and the output size is 2. The parameters WeightLearnFactor, WeightL2Factor, and BiasLearnRateFactor have all been set to 1, while BiasL2Factor is set to 0. WeightsInitializer and BiasInitializer have been initialized using the Glorot and zeros processes [18].

Convolution 2D Layer: Convolutional 2D (Conv2D) artificial neural networks are utilized for image and video recognition. A Conv2D layer extracts features from 2D input by convolutionally applying a sliding convolutional filter-kernel. Kernel filters extract edges and textures from the input image, which are employed in subsequent layers for object detection or categorization. CNNs use several Conv2D layers, pooling, and activation layers to construct deep neural networks that can recognize complicated image and video patterns. CNNs use the Conv2D layer, which is effective in a variety of image recognition and processing tasks.

Output Layer: The YOLO model architecture used can affect the output layer of YOLO v8. Generally, the output layer of a YOLO model architecture produces a tensor that represents the detected objects and their properties in an input image.

Figure 3 shows the several layers that make up the CNN model: the input layer, the convolution layer, the pooling layer, the fully connected layer, and the output layer. Images are offered as input for a plant disease

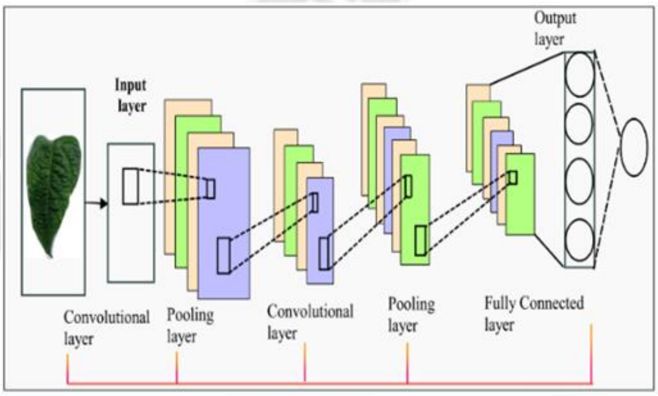

Figure-2: CNN

C. Training The Model

Installing the YOLO package requires downloading the 'YOLOv8' code from GitHub and then cloning the repository. 'YOLO v8,' the most recent version, is supported by Torch right now, and with the help of 'Google Collaboratory,' it may be

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readily implemented. On the system, this action will result in a new folder being created and given the name "YOLOv8."

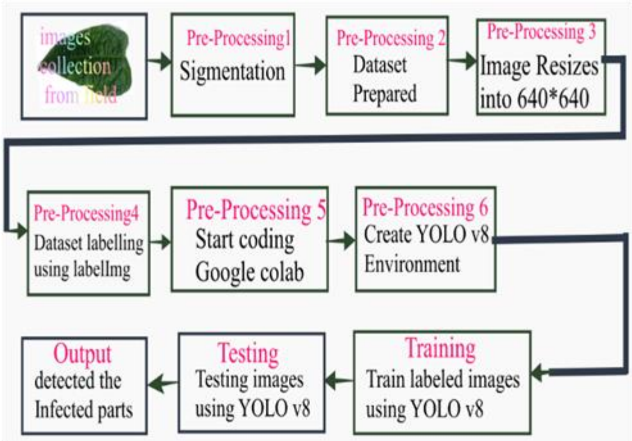

Figure-3: depicts the Basic diagram of both train and test YOLOv8 model.

This brand-new folder is going to be used to contain the pre-trained weights of the model as well as the unique YOLO directory structure. After training is over, YOLOv8 creates a new subdirectory in the Documents section. It is necessary to use the notation 'YOLOv8/run/training/ experiment/weights/last.pt' in order to include the path that specifies the location of the subdirectory. The 'yaml' document that was used here will be utilised to determine the appropriate adjustments to be made to the dimensions and weight of the document.

D. YOLO v8 Architecture

YOLOv8, the most recent iteration of the YOLO object detection method [19], has an architecture that is made up of numerous critical components, such as a Backbone, an SPPF (Spatial Pyramid Pooling Fusion) layer, a C2f (Convolutional Couple Filter) module, and a Detection module. These are the components that make up the architecture. The processing of the incoming image and the extraction of high-level features are both the responsibility of the Backbone. The SPPF layer is a multi-level pooling process that computes feature at different scales [20]. This provides the algorithm with the ability to recognize objects of varying sizes. The C2f module is an innovative technique that links two convolutional filters into one, making it possible for the algorithm to learn more complicated features in a time efficient manner. The Detection module uses the features generated by the other parts to estimate the bounding boxes and class probabilities associated with each grid cell. The YOLOv8 architecture is designed to support any YOLO architecture, not just v8, and it offers performance that is on par with the very best in its field when it comes to object detection.

IV. DATASET

The "new plant diseases dataset" is an example of the data type that may be used to train a convolutional neural network model YOLO v8. The training photos are from the batch of 202. Images of crop leaves, including black gram, in various health states. The collected photos are then classified into disease and healthy categories to identify unaffected leaves from those harmed.

Plant leaf photos are collected from the black-gram field concerning various stages of plant stages. These high-resolution images are cleaned by removing the blurred and inappropriately captured images. After cleaning, all the images have performed segmentation. LabelImg application software is used to label the images and then store in the yolo format. And it is observed that labelling is affecting the accuracy of the detection. So, It necessary to maintain the effective labelling of the images to ensure the good training the model for better accuracy. Figure-4 show the collection of black gram crinkle leaf's collected in the field of black gram.

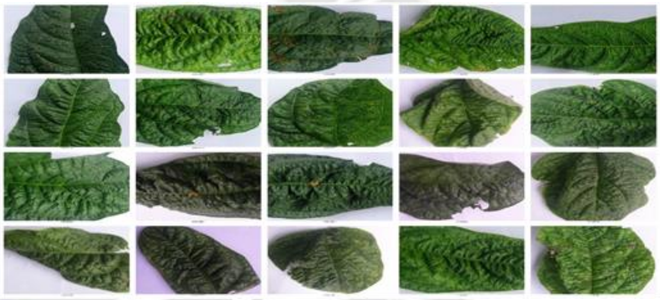

Figure-4: Crinkled Leaf Dataset

V. RESULTS

To better identify leaf diseases, researchers are trying out the convolutional neural network (yolov8). The database is split at 80/20, creating training and testing datasets. The CNN can tell if a leaf is healthy or diseased; if it is, it can also anticipate the type of disease. In 100,200,3000 iterations, a CNN model was trained and predicted with high accuracy. The results of the CNN model's training on the testing dataset are shown in Figure-5. Here in the image disease objects are identified and labeled with the boundary boxes.

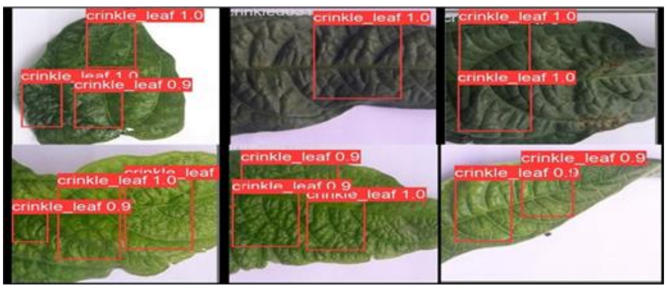

Figure-5: YOLO v8 Model Results

Machine learning uses precision and recall to evaluate classification algorithms. Recall measures how well an

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algorithm is able to identify true positive cases, whereas precision measures how accurately it makes positive predictions. High precision and recall imply the system can accurately identify most positive cases. Following figure-6 show the training and validation performance.

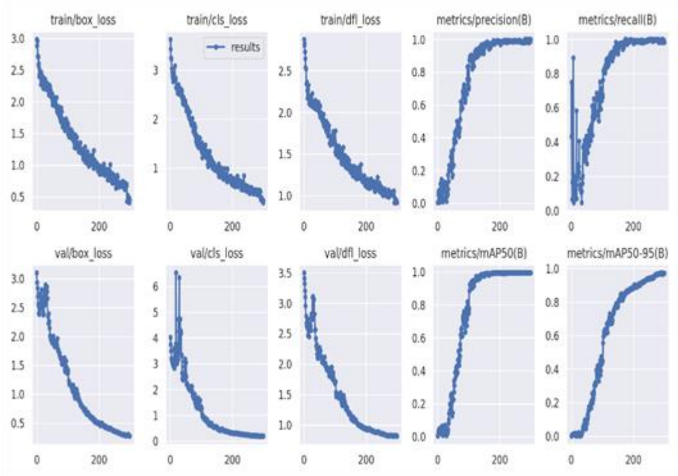

Figure-6: Results of Precession & Recall

The mAP50-95 metric evaluates the average precision across all classes and IoU (Intersection over Union) levels, revealing how well an algorithm can recognise objects of different sizes and forms.

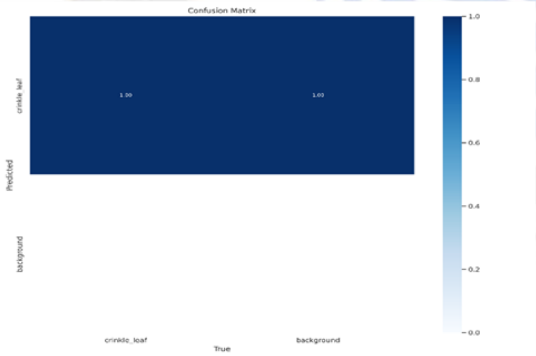

Figure-7: Confusion Matrix

The confusion matrix for the test set has a value of 1, which indicates that the model successfully categorized all of the sick leaf images that were included in the test set, which was taken from the 202-image dataset. The accuracy of the model was demonstrated by the absence of any incorrect classifications made in the diseased leaf category. The outstanding performance of the model in disease detection is demonstrated by the fact that each predicted occurrence is consistent with the actual class. The effectiveness of a machine learning model can be measured via a confusion matrix. It is commonly used in supervised learning, where the model is trained with labelled data, and is meant to evaluate the model's classification accuracy. The matrix displays the percentage of accurate predictions and the percentage of wrong predictions made by the model for each class. That is, it details the ratio of accurate diagnoses to false alarms, and vice versa. Accuracy, precision, recall, and F1 score are only some of the metrics that may be gleaned from the confusion matrix. In the above confusion matrix (see figure-7), we observed the good performance.

Machine learning uses the F1 score to assess model accuracy. It is a weighted average of accuracy and recall, where precision is how often a model predicts something correctly and recall is how often it predicts something correctly out of all the times it should have. F1 is 2*(precision*recall)/(precision+recall). The best score is 1. Classification models that predict the correct label for a given input are evaluated using it.

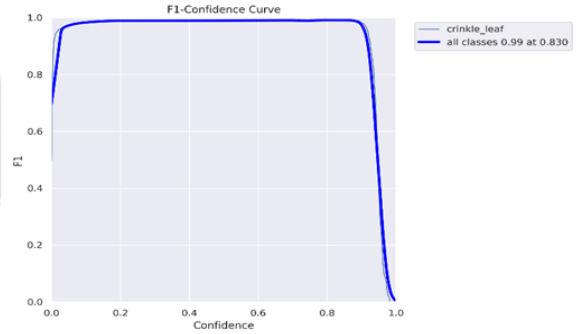

Figure-8: F1 Curve

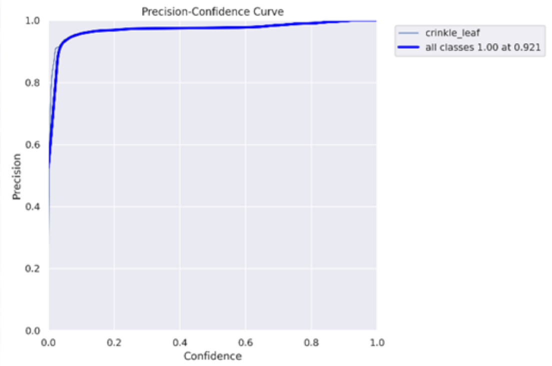

Figure-9: P Curve

The F1 confidence curve, which ranges from 0.99 to 0.83, demonstrates the model's ability to reconcile precision and recall across different confidence thresholds. The high values of the curve indicate the robustness of the model in correctly identifying instances of crinkled leaf disease while minimizing false positives.

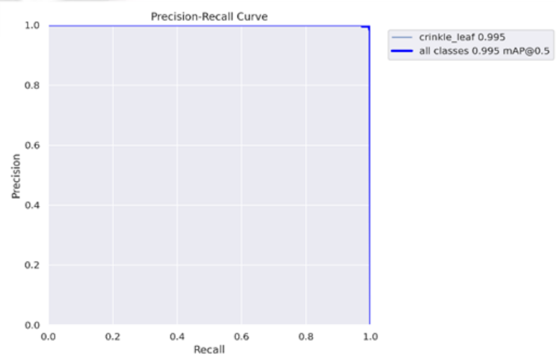

Figure-10: PR_Curve.

The Precision-Recall (PR) curve values, specifically an average of 0.995, indicate the model's remarkable precision in

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recognizing real positive cases while maintaining high recall rates. The accurate identification of diseases is of utmost importance in the field of disease detection, as the consequences of both false positives and false negatives are quite substantial. The model exhibits remarkable precision and memory capabilities in identifying sick leaves from the test data, as evidenced by its high AP and mAP scores. Hence the proposed model is showing the improved performance compared to the earlier models in the area of object detection.

Figure-11: R_Curve

VI. CONCLUSION

The use of image processing and machine learning in the diagnosis of disease is becoming increasingly common. Datasets such as "new plant disease dataset" can be utilized to train convolutional neural network models like YOLO v8. This study's findings support the usefulness of the YOLO v8 model for identifying black gram crinkled leaf disease. A total of 202 images of healthy and diseased blackgram leaf samples were used to train the model. A total of 80% of the data was used for training the model, while 20% was used for validation. When segmenting the leaf disease region, a grey-level co-occurrence matrix (GLCM) is used to retrieve the image's distinctive features. A fragment of the leaf was discovered, and YOLO was able to identify it. High values on the F1 confidence curve and an average of 0.995 on the PR curve demonstrate the mod-el's precision and consistency in disease diagnosis. The model's excellent performance is further supported by the perfect confusion matrix value, which indicates accurate classification of diseased leaf samples. The success of this research is crucial for agricultural applications since it will provide a reliable method for the early detection of diseases. By helping farmers make focused interventions and minimizing output losses, early detection of crinkled leaf disease is an important part of effective crop management. As can be seen from the evaluation criteria, the model has a high degree of accuracy, making it a valuable asset for precision agriculture and maybe ushering in a new era of disease surveillance in the agricultural industry. It is crucial, however, to keep honing the model and investigating its robustness across a variety of contexts and illness stages. Further increasing its practical utility and guaranteeing its smooth absorption into agricultural practices is the incorporation of the model into user-friendly software for real-time disease monitoring.

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