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Leaf Disease Predictions Using Deep Learning Techniques - Potato

M.K. Deepna[1], P. Bavithra Matharasi[2]

[1,2]Department of Computer Science, Mount Carmel College, Autonomous, Bengaluru, Karnataka, India, 560052

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ABSTRACT

The Study of leaf diseases is important to obtain healthy crop yields and confirm food security. Detection of potato leaf diseases at an early stage is of great significance to the agricultural industry. Detecting this disease early helps farmers protect their plants. But soil and climate pollution are highly unfavorable for
potato growth and it leads to disease such as scab, black scurf, blackleg, dry rot, and pink rot. Though, identifying diseases in potato leaves is challenging because of the composite symptoms and variability in leaf presences. This involves the advance of an operative and efficient method that can overcome these contests and improve disease detection accuracy. Predicting potato leaf disease at early stage is crucial and this research paper proposes a deep machine learning approach utilizing Convolutional Neural Network Especially Residual Network50 Version 2(ResNet50V2) model that can rapidly and accurately identify plant disease. The comparative study of the leaf disease works on three models CNN, EfficientB0, ResNet50V2
model. Comparing these models the study reached the expected testing and train accuracy. The study highlights the importance of feature fusion and predicting early leaf disease in enhancing disease diagnoses.

Corresponding Author:

M. K. Deepna
Department of Computer Science
Mount Carmel College, Autonomous
Bengaluru, Karnataka, India, 560052

Email: mkdeepna3@gmail.com

1 Introduction

In worldwide food production, cultivation plays a major role and one of the most sophisticated crops are potatoes. Crop yield quality is disturbed by leaf disease. It makes primary and exact recognition crucial for farmers. Using advance machine learning techniques, this project apparatuses an automated disease detection system. The main cause for these viruses is fungi, bacteria and diseases. [3]. Biotic and abiotic are the main causes of leaf diseases. Crops are contaminated by killing plant cells. Digated seeds, crop rolls, in appropriate soil, weeds and other crops can cause fungal forms Infection. During the extension of a disease, the leaves may become internally ill by bacteria and no interior can show or external signal. The analysis can be challenging because it is difficult to detect viral impurities. Leafhoppers, white flies, cucumber beetles and insect virus spreads through these changes Insects [16].

The dataset includes early flash, late blight and health. Fugus leaves are caused by early blights, brown and black spots leading to yellow and yellow Decision are symptoms of early blight. The most devastating potato disease is late blight. If there are no symptoms, the leaves are healthy. The greatest effect of potato leaf disease is that the leaves cannot produce enough energy (reduced photosynthesis). Serious infections can destroy the entire regions that are nothing, but loss of return. Environmental circumstances are critical. Potato growth takes residence in moderate rainy regions, creation climate adaption a significant feature.

Planting potatoes can present challenge in parts characterized by advanced temperatures or a low water source, which might straight affect complete consumption levels. The entire consumption of potatoes is precious worldwide because of approximately dietary habits produced by cultural and environmental limitations. Analyzing these variations offer an added thoughtful of the complex factors manipulating food [8].

This paper uses a deep learning model, especially CNNs like the ResNet50V2 model, that offers an efficient potato lead disease detection automatic solution. The ResNet50V2 model provides high accuracy and efficiency in image classification tasks for this dataset. This model prevents vanishing gradient problems and speeds up training. This ResNet50V2 model provides the implementation of potato leaf disease detection, a robust, efficient, and scalable solution for detecting disease early. That helps the farmers protect crops and increase their productivity.

1.1 Research Problem and Significance

This research seeks to solve the following research question:

"How effectively ResNet50V2 classify predicting Potato Leaf disease in early stages, which is useful for farmers."

Potato crops are extremely vulnerable to various leaf diseases, such as Late Blight, Early Blight, and healthy, which can meaningfully decrease produce and value. Traditional disease gratitude means rely on guide inspection, which is inefficient, labour- intensive, and prone to anthropological error. Late recognition mainly leads to financial loss for farmers, severe crop harm and improved use of chemical pesticides.

To overcome this challenge there is a need for accurate, automatic and efficient potato leaf disease estimating system using deep learning performances. It can be achieved by early disease recognition through double analysis, allowing farmers to take sensible preventive measures. The aim of this research is to improve early finding of potato leaf disease and enables farmers to take appropriate actions to decrease crop disease and improve production. By inculcating deep learning, this research aims to the progress of systematic disease detection systems which funds precision farming, minimizes relying on chemical pesticides and promotes agricultural performs. In this research they predicted potato leaf disease with an enhanced presentation grade by incorporating image separation systems and deep learning algorithms [18].

Comparison

The conventional CNN-based methods tend to suffer from excessive computational complexity, data privacy, and class imbalance, which curtail their efficiency and interpretability. To counter these challenges, this study presents an improved deep learning architecture that incorporates sophisticated preprocessing and data augmentation methods to enhance dataset quality. Through the application of ResNet50V2 for feature extraction, the model achieves considerable reductions in computational overhead over CNN-SVM hybrids and federated learning methods. In addition, dynamically computing class weights reduces bias against majority classes, and balanced classification performance in ensured. Then method not only improves model interpretability but also preserves high accuracy, and the solution turns out to be more efficient and robust for potato leaf disease detection.

Table 1: Comparison

Title	Model & Accuracy	Research Gap
Advanced Techniques for Sweet Potato Leaf Disease Detection: A CNN-SVM Hybrid Approach	CNN & 88%	Does not address the computational complexity
DetectPLD: A Federated CNN Approach for Collaborative Potato Leaf Disease Detection	CNN & 93%	Enhances data privacy and not addressed model convergence issues

Implements detailed preprocessing and augmentation, improving dataset quality. ResNet50V2 for feature extraction, reducing computational cost compared to CNN-SVM and Federated Learning. It improved Model Interpretability. Calculate square load dynamic to reduce prejudice against majority classes.

2 Literature Survey

Various studies have been done on the expansion of agriculture, and it can be improved in economic growth and proposes a strong environment for humans. Deep learning models and data vision based instructions have been used more to increase crop production. In this section, an inspiring offering is offered to know about the previous study task [18].

Research evaluates several determination nerve networks (CNN) Architecture including Mobilnetv2, Reset50, VGG19, VGG16 and Potato Leaf Disease predictions for Alexnet. The main is to highlight the efficiency of the main reset50 in this letter. This is a lot of accuracy in classifying potato leaf disease. The results which we obtained shows that ResNet50 performed best with a very high 97% testing accuracy and 98% specificity. On the other hand, the VGG19 system was the worst performing. One main issue is to correctly classify healthy leaf categories which reflects a possible areas of model improvement. The outcome of this research is to provide a hopeful avenue for direct diagnosis of potato leaf diseases to make a way for better crops and improved agriculture yielding [2]. The name of the paper Collaborative Averaging with DenseNet201, is a grouping of ResNet50V2 and

DenseNet201 model to identify potato leaf diseases. This paper collected the datasets of 5702 images from the Plant Village Potato dataset. The datasets contain of 3 classes training, validation, and testing. The test sets run over 5 epochs, by addition 3 dense layers to individually model. The K-means clustering technique is used moreover, the disease is examined by pixel damage, categorizing severity when over 50% of pixels were artificial. Literature also exposes that in the arena of Potato

Leaf Disease Prediction, most of them used CNN, VGG, ResNet50 and DensNet201 models. They got high accurateness when combing the models. High precision is got in CNN model. In this paper used only ResNetV2 model and got better accuracy when compared these papers. The primary focus of this paper is unseen data.

3 Methodology

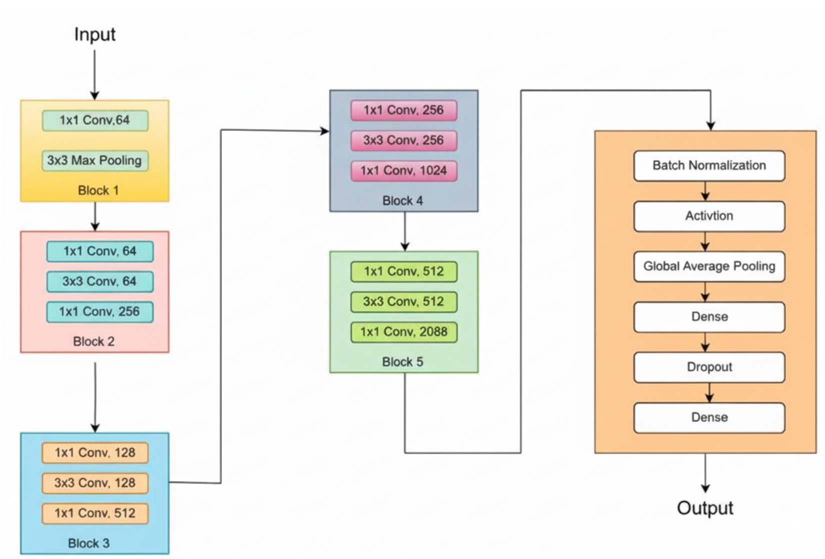

Figure 1: ReNet50V2 Architecture

Fig. 1 shows the model is manufactured consuming ResNet50V2 as a base feature extractor and also custom layers for classification. The total layers used in ResNet50V2 model for potato leaf disease prediction is 193 layers (190 is ResNet50V2 + 3 is Custom). The feature extractor removes the default fully connected layers. The input images extract the deep feature. The pre=learned weights from ImageNet are frozen. Global Average Pooling Layer reduces feature maps into a single feature map. The global feature representation converts a spatial feature. The Dense layers are fully connected layers with 128 neurons and ReLu activation. It learns complex relationships from the extracted features. Dropout layers of 50 % prevents overfitting. It randomly drops neurons during training. Dense SoftMax is the final output layer, which produces the probability scores for each class.

3.1 Dataset

The dataset is a collection of potato leaf disease images (PLD_3_Classes_256). The data set images contain 256x256 pixels in size. Data is classified into three separate classes depending on the type of disease. To prepare, approve and test the information, it is divided into training (model training) by three organizers, tests (setting of hyper proses) and verification (final model assessment). The dataset covers healthy, early flash and late blights. Potato leaves are not infected, they are known as a healthy class. Early bleach leaves are affected by dark spots with rings of trains. Sent blight leaves are affected by irregular brown spots with yellow glory. Exercise, verification and test data contain images (early blight, healthy, late blight).

Table 1 describes the dataset of Figure 1 (a)-(c) Early Blight, Late Blight and Healthy potato leaf images. Owing to the limited quantity and imbalance of images, additionally, 3,251 photos from Pakistan's Central Punjab were included in the PLD dataset. This dataset contains 816 healthy images, 1,303 early blight images, and 1,132 late blight images after redundancy has been removed. All photos are saved in uncompressed JPG style and have RGB color profiles [1].

Table 2: Description of the dataset

Label	Training	Validation	Testing	Total
Potato early Blight	1303	163	162	1628
Potato Late Blight	1132	151	141	1424
Healthy	816	102	102	1020

3.2 Data Preparation (Preprocessing Techniques)

Pre-processing plays an important role in boosting the quality of images before subjecting them to potato disease classification algorithms. Resizing and normalization are two fundamental techniques used in this process. Resizing connection to change the dimensions of images to a uniform size, which aids in reducing computational complexity and ensuring consistency across the dataset.[14]

3.2.1 Image Resizing

In order to have a consistent input dimension for the model, all the images are resized to 224x224 pixels. Here fixed-size input deep learning models are needed which are needed in order to standardize image sizes. Images are resized in order to minimize the computational complexity as well as to remain compatible with the pretrained models such as ResNet50V2

3.2.2 Image Normalization

To image Pixel values are normalized between 0 & 1 range for effective model training. Normalization makes sure that all the input data lies within a comparable numerical range and avoiding some pixel intensities from dominating learning process. Which enhances gradient descent efficiency, resulting in faster and more stable training. Image processing algorithms can variation the image brightness, contrast, and sharpness, strongly touching human and machine perception. In this study, the Wiener and total variation denoise filters were used for denoising, while the unsharp mask sharpening filters were utilized for deblurring [7].

3.2.3 Duplicate Image Removal

To eliminate the duplicate images, Perceptual Hashing (pHash) is utilized. The algorithm employs distinct hash values for images and on the basis of similarity scores eliminates the images of the duplicates. Removal of duplicate images avoids over-representation of some classes, making the dataset balanced.

3.2.4 Blurry Image Detection and Removal

The Laplacian Variance Method is used to calculate sharpness. This image can be degrading model performance as they contain less distinguishable features. If the image has a variance below a defined threshold (BLUR_THRESHOLD=50) classified as blurry and removed. This was used only for clear and high-quality images are used for training.

3.3 Data Augmentation

This technique improves the robustness of the model by expanding artificially with various transformation of the dataset. Rotation helps the model to recognize the diseased leaves from different orientations. It changes the camera angles during real-world image capture. Height and Width shifts that simulate different image positioning. The dataset is augmented with vertical and horizontal shits. The model can accurately classify leaves in varied placements. Brightness adjustments of images are randomly increased or decreased within a 0.8 to 1.2 range; the lighting conditions can vary in real-world scenarios. So, brightness augmentation is used. The model is designed to classify diseases under different lighting conditions. In the real -world scenarios, the leaves can turn due to the pattern of natural plant growth. Horizontal flipping counter orientation by reflecting the leaves of the leaves, while the cut easily replaces the size of images, the camera simulates the variation in angle and distance. This image growth technique plays an important role in reducing and increasing the accuracy of the model for classifying potato leaf disorders.

3.4 Feature Extraction:

Functional extraction: Functional extraction involves taking advantage of a pre -tested model to capture high -level functions from images, instead of creating a model from scratch. In this case, the Reset50V2 function acts as an extractor, which is supplemented with customized layers to effectively classify the features that have been extracted.

3.4.1 Model Building:

Resnet50V2 is a version of the Resanet50, suggested by Microsoft Research, is a sophisticated deep learning architecture for image classification and functional extraction. It adapts to deep residual networks by solving the fading of the gradient problem through shortcut compounds, so that gradients can propagate more efficiently during training. While Resnet50V2 uses a pre -cycling architecture where activation in batch normalization comes in front of the function, leading to the gradient flow, stable training and better model accuracy. Architecture includes 50 layers of residual connections held in four steps with traditional layers, normalization of batch, Relu activation and 1x1, 3x3 and 1x1 bottleneck blocks. The network begins with a 7x7 affects layers and max -pulsation, processing input through several remaining layers, and ends with a fully associated layer for global average pool and classification. The Reset50V2 has several advantages to the ResNet50, including better spread of shield, increase in accuracy and sharp convergence, making it a strong model for intensive learning applications. This is widely used in most functions such as image classification, object detection, medical imaging, face identification, autonomous vehicle and satellite image treatment. Nevertheless, the model comes with a few deficiencies, including high calculation expenses, use of high memory and overfit on small datasets, if not well regulated. Despite these obstacles, the recanet50V2 is extremely effective for learning transmission, as the strong plant allows the production capacity developers to set it for specific datasets. It is easy to use the recanet50V2 with TensorFlow or keras, so model is an option for complex image recognition and classification works.

4 Results

4.1 Visualization

Fig. 2 shows the visualization image of the model classifies the predictions for potato leaf disease detection. The image's layout is a grid of 10 potato leaf images and it is arranged in two rows of five. The leaf image has two labels-True label and Predicted label. True label is the actual class of the leaf for example Early Blight. The predicted label is the classification output. It is observed that the most of the predictions are correct and the Early Blight is predicted as Early Blight. Some of the classifications are present and there are few cases where early blight was detected as late blight and one case where early blight was detected as healthy.

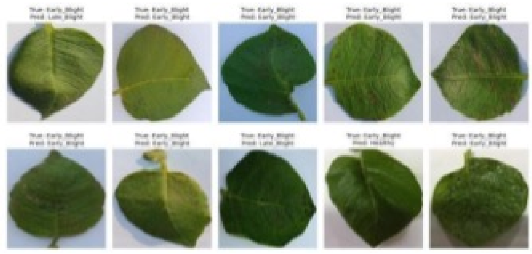

Figure 2: Visualization of the potato leaves

4.2 Confusion Matrix:

Table 2. shows a potato leaf disease classification model performance is assessed using the image of confusion matrix. The number of predictions the model made for each class is indicated by the cell in the matrix. Early Blight, Late Blight, and Healthy are the three classes that are used to predict the model. The class that the model predicts is represented by the Predicted labels (Columns). The actual leaf is represented by the True labels (rows). Misclassified samples are represented by the off- diagonal values. The bolded diagonal values represent accurate predictions.

Table 3: Structure of the Confusion Matrix

True Label/Predicted Label ->	Early Blight	Healthy	Late Blight
Early Blight	146	3	13
Healthy	1	94	7
Late Blight	0	4	137

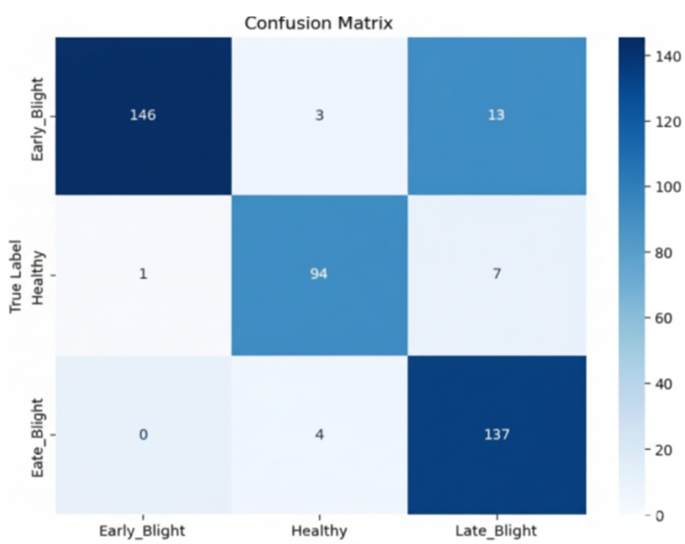

Figure 3: Confusion Matrix

4.3 ROC Curve

The Receiver Operating Characteristic curve is a graphical representation of a classification model's ability to distinguish between classes. The performance metrics provides output for a multi- class classification model used for potato leaf disease detection.

Fig 3. Shows the image of the confusion matrix can observe that Early Bight Predictions are 146 classified correctly as Early Blight, 3 misclassified as Healthy and 13 misclassified as Late Blight. The Early blight model shows that Early blight with Late blight more than Healthy. The Healthy predictions are 94 classified correctly as Healthy, 1 misclassified as Early Blight and 7 misclassified as Late Blight. The Healthy Predictions model shows that Healthy leaves with Late Blight. The Late Blight Predictions are 137 classified correctly as Late Blight, 4 misclassified as Healthy. The Late Blight Predictions model rarely confuses Late blight with Early blight which is good.

4.3.1 Precision

Measures how many positive predicted cases are actually correct.

$Precision = \frac{TP}{TP+FP}$

4.3.2 Recall (Sensitivity, True Positive Rate)

Measures how many actual positive cases were correctly identified.

$Recall = \frac{TP}{TP+FN}$

Both the classes of Healthy and Late Blight have AUC values of 0.99 shows the near perfect discrimination. The ROC curves are close to top left corner reflecting high sensitivity and low false positive rates outperforming the random guessing (AUC=0.5). Late Blight has lower precision (0.87) but higher recall (0.97) it shows rarely misses the true cases but occasionally misclassifies other categories as Late Blight. Early Blight has high precision (0.99) but slightly recall (0.90) some true cases are missed. The Healthy class maintains a balance with precision (0.93) and recall (0.92), with an overall accuracy of 93%.

Table 4: Classification of ROC Curve

Class	Precision	Recall	F1-Score	Support
Early Blight	0.99	0.90	0.94	162
Healthy	0.93	0.92	0.03	102
Late Blight	0.87	0.97	0.92	141

4.3.3 4F1- Score

Harmonic mean of precision and recall, balancing false positives and false negatives.

$F1Score = \frac{2XPrecisionXRecall}{Precision+Recall}$

4.3.4 Support

The number of actual instances for each class in the dataset.

Table 4. Shows the model classification performance excellently, indicating perfect classification with an AUC of 1.00 for Early Blight.

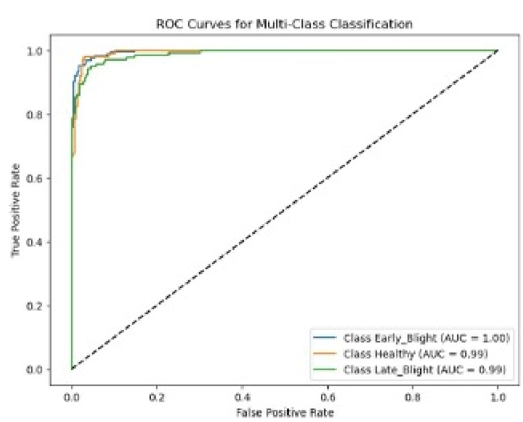

Figure 4: ROC Curve of Multiple class classification

4.4 Plot Accuracy & Loss

Fig 5. the plot Accuracy and loss visualize the model performance over multiple training epochs. The left plot is Training and Validation accuracy. The X-axis (epochs) are the number of models seen in the training data. The Y-axis is the model predicts correctly (between 0 to 1). The Train Accuracy which is in blue line is training data. The training data is consistently high of 96% where the data is trained well. The validation Accuracy which is in orange line is testing data. The accuracy of validation is (92%-93%), which is lower than the training accuracy saying that some overfitting. Fig 4. Shows the Plot contains ROC Curves for three classes in a multi-class classification problem, Early Blight is in blue color of AUC=1.00, Healthy is in orange color of AUC=0.99, Late Blight is in green color of AUC=0.99.

Early Blight, Late Blight. The prediction of the mode shown image as "Early Blight and Late Blight" which means the detected indicators align with this disease period. Though, it's always a good idea to confirm with domain specialists or use multiple images for better accuracy.

Figure 5: Leaf Sample

4.5 Unseen image prediction

In Fig 6. the random image was taken and processed in a deep learning model trained to classify potato leaf diseases into three categories like Healthy.

Figure 6: Predict the image

5 Discussion

The results from the potato leaf disease classification determine its efficiency in exactly recognizing three key categories: Early Blight, Late Blight, and Healthy leaves. The visualizations, concert metrics, and qualified assessments afford visions into the model's strengths and limitations.

5.1 Model Classification Performance

Visualization of Fig. 2 is indicative of the fact that the model is accurately classifying most potato leaf images, especially Early_Blight. The model makes misclassifications sometimes, ascribing Early_Blight to Late Blight or Healthy at times. This is an indication of finding it challenging to separate early signs of blight diseases based on their appearance similarity. Confusion matrix (Table 2, Fig. 3) confirms this, that even though the model is solid, it finds it hard to differentiate between Early and Late Blight.

5.2 ROC Curve and Classification Metrics

ROC curve analysis (Fig. 4) demonstrates the discriminative ability of the model to be very high, with an AUC value of 1.00 for Early Blight and 0.99 for Healthy and Late Blight. Precision, recall, and F1-score values also support the reliability of the model. Though Late Blight registers a good recall (0.97), it incorrectly classifies other classes as Late Blight at times. On the other hand, Early Blight is highly precise (0.99) but less so in terms of recall (0.90), and some actual cases are not captures. The Healthy class has a good precision- recall balance, resulting in a 93% overall accuracy.

5.3 Dataset Distribution and Model Generalization

The class distribution plot (Fig. 5) shows a uniform distribution of images in training, testing, and validation sets to avoid bias towards any specific class. This balance improves the generalization ability of the model. The accuracy and loss plots (Fig. 6) reflect stable training performance with training accuracy up to 96% and validation accuracy between 92% and 93%. The small gap indicates minimal overfitting, which may be avoided by data augmentation or regularization methods.

5.4 Real-World Application and Unseen Image Prediction

The model performance on unseen images (Fig. 7) shows its relevance to actual situations. IT accurately classifies an unidentified leaf sample into the right disease category, affirming its validity. Even so, in view of the intricacy of plant diseases and potential symptom overlaps, expert verification is advisable for high-stakes decision making. Potential future improvements may incorporate environmental conditions, multispectral imaging, or hybrid models blending deep learning with traditional classification methods to enhance accuracy even more.

6 Conclusion

The study presents a deep leaning-based approach using a fine-tuned ResNet50V2 model for potato leaf disease prediction. Agriculture is the most important economic aspect of our country as the majority of the common people have heavily relied on agriculture. A classification-based approach to identify late blight, early blight and healthy leaf images of potato plants using deep learning techniques and the ResNet50V2 model. The discovered that ResNet50V2 works well for this kind of item classification. Got the accuracy of test accuracy at 93 % and train accuracy is 96%. The Indian village farmers lack literacy and have incomplete knowledge of the disease. This work has the potential to alter the farmer.

Future work contributes to automated plant disease prediction. This is help full for farmers and researchers in early disease diagnosis, which is crucial for plant health monitoring and yield improvement. And also work on real-time deployment, computing integration and hybrid deep learning models to enhance scalability and real- world application. The researchers can work on the latest models to now the models work better and get best accuracy.

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