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An Efficient Disease Detection System for Providing AI-Driven Precautions for Crop Yield

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Abstract: Plant diseases pose a significant threat to global agriculture, affecting crop yields and jeopardizing food security. In this study, we present a novel approach to address this issue through the utilization of Convolutional Neural Network (CNN) models for plant disease detection. Our research focuses not only on the accurate identification of plant diseases but also on providing practical precautions and solutions to assist small-hold farmers in maximizing crop yield capacity. By enabling early disease detection and offering actionable guidance, our approach contributes to reducing financial losses, enhancing food security, and supporting the sustainability of small-scale agriculture. Early detection of plant disease can help in ensuring food security and controlling financial losses. The images of diseased plants can be used to identify the diseases. Classification abilities of Convolutional Neural Networks are used to obtain reliable output. Such techniques are widely used and proved beneficial to farmers as detection of plant disease is possible with minimal time span and corrective actions are carried out at appropriate time. In this paper, the performance of a pre-trained ResNet34 model in detecting crop disease is investigated.

Keywords: Deep Learning, Transfer Learning, Classification, CNN, Plant Disease Detection, Resnet Architecture, Precision Agriculture.

1. INTRODUCTION

A. Motivation

Agriculture is the backbone of our global food supply, and ensuring a bountiful crop yield is paramount for food security. However, plant diseases continue to plague farms, causing significant losses in crop production and threatening the livelihoods of farmers. In this digital age, the integration of advanced technologies like Artificial Intelligence (AI) has proven to be a game-changer in mitigating these challenges. This paper introduces an innovative and

efficient disease detection system that harnesses the power of AI, not only to accurately identify plant diseases but also to provide AI-driven precautions aimed at enhancing crop yield.
The conventional methods of disease detection in agriculture are often labor-intensive and time-consuming, making it chal-lenging for farmers to respond swiftly to emerging threats. This system leverages AI's capacity to analyze vast datasets of images, swiftly and accurately identifying diseases in plants.

B. Objectives

1. To include more types of plant diseases in our project to help more farmers.
2. To make the results more accurate by improving how the system works.
3. To make it even better, we should add more information to the database so the system can recognize more diseases.
4. Right now, the system can only tell if a plant is sick, but it doesn't tell us how to make it better.

2. LITERATURE SURVEY

In the paper —Deep learning for Image-Based Plant detec-tion" [1] the authors Prasanna Mohanty et al., has proposed an approach to detect disease in plants by training a convolutional neural network. The CNN model is trained to identify healthy and diseased plants of 14 species. The model achieved an accuracy of 95.35% on test set data. When using the model on images procured from trusted online sources, the model achieves an accuracy of 31.4%, while this is better than a simple model of random selection, a more diverse set of training data can aid to increase the accuracy. Also some other variations of model or neural network training ma yield higher accuracy, thus paving path for making plant disease detection easily available to everyone.
Malvika Ranjan et al. in the paper —Detection and Clas-sification of leaf disease using Artificial Neural Network" proposed an approach to detect diseases in plant utilizing the captured image of the diseased leaf. Artificial Neural Network (ANN) is trained by properly choosing feature values to distinguish diseased plants and healthy samples. The ANN model achieves an accuracy of 80%.
According to paper —Detection of unhealthy region of plant leaves and classification of plant leaf diseases using texture features" [3] by S. Arivazhagan, disease identification process includes four main steps as follows: first, a color transformation structure is taken for the input RGB image, and then by means of a specific threshold value, the green pixels are detected and uninvolved, which is followed by segmentation process, and for obtaining beneficial segments the texture statistics are computed. At last, classifier is used for the features that are extracted to classify the disease.

3. PROPOSED METHOD

There are various models of CNNs available which can be used to for leaf disease detection.

1. Le Net
2. Alex Net
3. Vgg Net
4. Res Net

We have used Res Net as main model it has 99.2 among all the tested model. In this Project. We divided the dataset into training, validation and testing part.

A. Data Acquisition

'The PlantVilllage Dataset' [35], an open-access repository which contains images. These images contain additional plant anatomy, in-field background data and varying stages of disease disease detection, we consider the PlantVillage dataset. Specifically, The dataset contains 87,000 RGB examples of healthy and diseased crops, which have a spread of 38 class labels assigned to them. An example batch of the PlantVillage dataset is shown in Fig. 4. We perform both the model optimization and predictions on these downscaled images.The dataset is divided into 80% for training and 20% for validation.

Fig. 1. An example batch of the PlantVillage Dataset

B. Pre-Processing on Image

Normally image is in RGB colour but before providing that image to the model we convert that image into grey scale with a single monochrome channel to avoid unwanted noise in the image. While giving input to the model user can provide image with the different size, so we need to convert that image to the specific size. Here we have used 255 X 255 pixel image. While storing the image into tensorflow we store it in the form of matrix.

C. Feature Extraction

If we want to remove some feature then its size will be reduced. In this process we can apply various operations such as pooling, Nor-malization and other operations. After extracting the feature we convert that 2D matrix into flatten array and pass that array to dense layer.

D. Classification by CNN

We perform experiments with three ImageNetpretrained models - VGG-16, ResNet-50, and GoogLENET. These mod-els have varying numbers of parameters, sizes, and perfor-mance on the ImageNet dataset. It has been shown that these pre-trained models perform better than a model trained from scratch on the PlantVillage dataset. A low learning rate is used to prevent the divergence of the model and to preserve primitive image filters identified during pre-training.

The batch size used during training is 32, and the number of epochs used is 25. In addition, we also use early stopping and model checkpointing based on the validation loss, which gives us the best-performing model on the validation dataset. We also note down the accuracy of the model during the training. The performance of these models may be further improved with training. The flowchart outlines a step-by-step process.

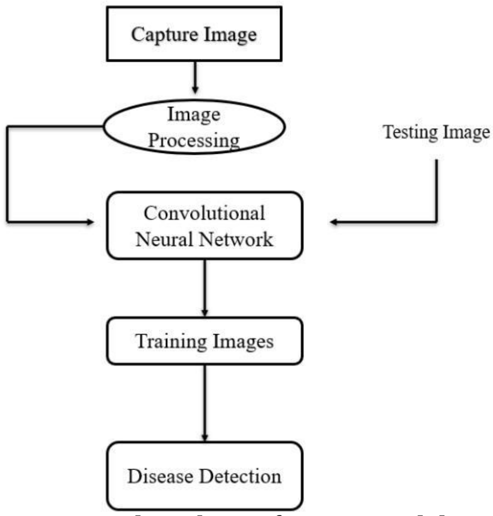

Fig. 2. Flowchart of CNN Model

For plant disease detection. It starts with capturing images of plant leaves, processes these images to make them suitable for analysis, uses a specialized neural network called CNN to learn how to recognize diseases from a large dataset, and then applies this learning to identify diseases in new images. This method is vital for creating automated systems that help farmers detect and manage plant diseases early.

Architecture of Convolutional Neural Network

A Convolutional Neural Network (CNN) comprises three essential layers: a convolutional layer, a pooling layer, and a fully connected layer. Figure 3 provides a comprehensive illustration of these layers working together.

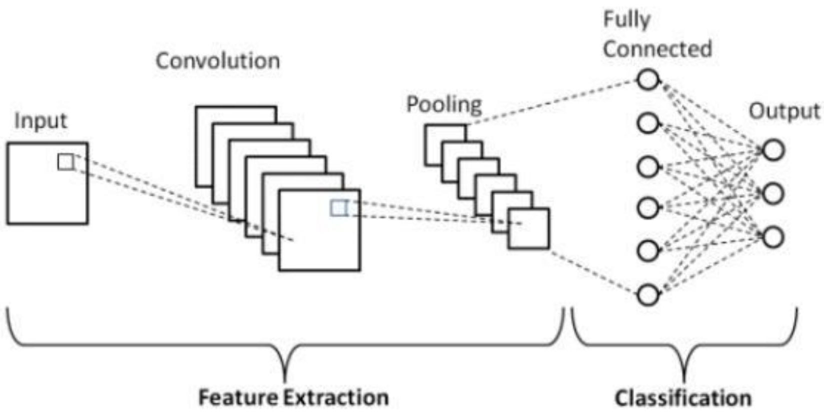

Fig. 3. Architecture of CNN

A. Convolutional Layer

The initial layer in a CNN network is the Convolutional Layer, serving as the foundational building block and responsible for the majority of computational work. It convolves data or images by applying filters or kernels. Filters are small units that we apply across the data through a sliding window.

The depth of the image is the same as the input, for a color image that RGB value of depth is 4, a filter of depth 4 would also be applied to it. This process involves taking the element-wise product of filters in the image and then summing those specific values for every sliding action.

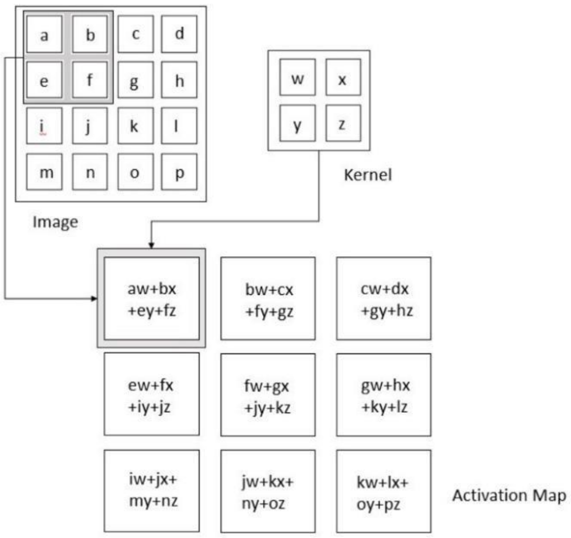

Fig. 4. Convolutional Layer

B. Pooling Layer

POOLING LAYER, which involves the downsampling of features. It is applied through every layer in the 3d volume. Typically there are hyperparameters within this layer.
The dimension of spatial extent: which is the value of n which we can take N cross and feature representation and map to a single value. Stride: which is how many features the sliding window skips along the width and height.

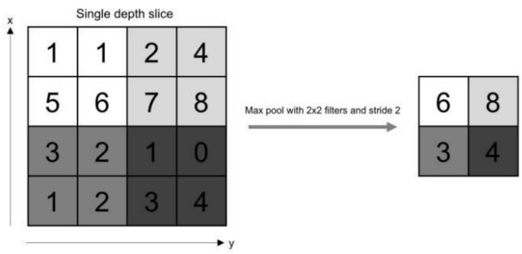

Fig. 5. Pooling Layer

C. Fully Connected Layer

Fully Connected Input Layer: The output from the preceding layers is "flattened," transforming it into a single vector that serves as the input for the subsequent stage. The first fully connected layer – adds weights to the inputs from the feature analysis to anticipate the proper label. Fully connected output layer – offers the probability for each label in the end.

Convolutional Neural Networks (CNNs) help detect diseases like plant diseases or medical conditions by looking at pictures. They're good at finding patterns and features that show if something is wrong. These patterns could be spots on plant leaves or abnormalities in medical images. CNNs can do this quickly and accurately, and they're consistent, so they give the same results every time. They're like smart assistants that can spot problems early and help experts make quick decisions to prevent diseases from spreading and causing harm.

4. RESULTS AND DISCUSSION

We have discussed the acuuracy and loss curves of the CNN models. we have examine Keras+CNN, LeNet, VGGNet and last one is ResNet. we will compare the accuracy and loss of the above model and one of the best model choose for the purpose the depolyment later.

A. Resnet Model

ResNet (short for "Residual Neural Network") is a family of deep convolutional neural networks designed to overcome the problem of vanishing gradients that are common in very deep networks. The concept behind ResNet is to incorporate "residual blocks," which facilitate the direct propagation of gradients throughout the network, thus enabling the training of extremely deep neural networks. A residual block typically comprises two or more convolutional layers, an activation function, and a shortcut connection. This shortcut connection serves to bypass the convolutional layers and directly add the original input to the output of these convolutional layers. This design enhancement greatly contributes to the network's ability to be trained effectively and efficiently

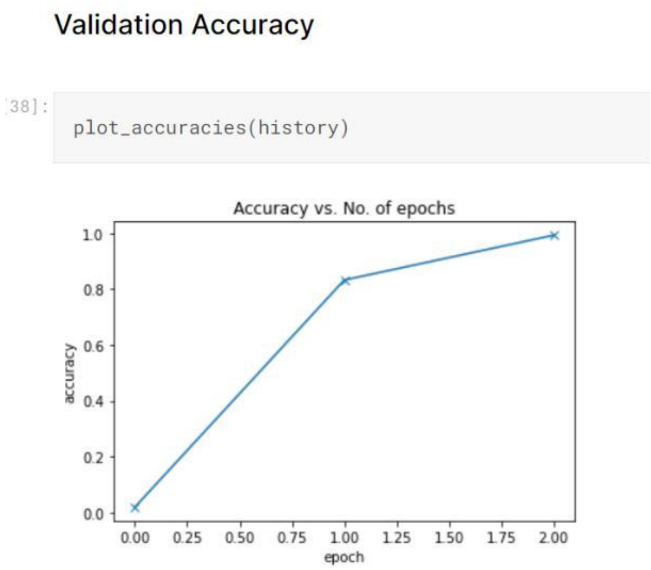

Fig. 6. Validation Accuracy in ResNet Model

A 99.2% accuracy rate was achieved using early stopping while Training the model on 2 epochs where Y-axis shows the accuracy and the x-axis shows the no. of epochs the trained model is tested on a set of images.

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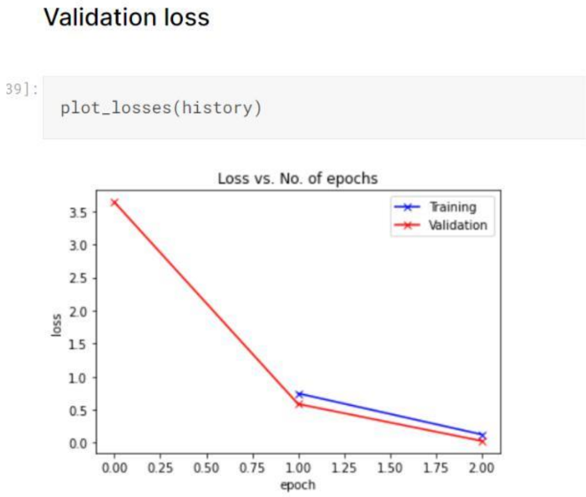

Fig. 7. Validation Loss in ResNet Model

We have plotted the accuracy and loss curves of this model which gives an accuracy of 99.1 and a loss of 2.6 curve which is the highest accuracy model among all where the y-axis shows the loss and the x-axis shows the epochs

Random images are introduced to the network and the out-put label is compared to the original known label of the image. algorithms to be able to generate better and more fine-grained explanations in a future work. This helps in understanding whether the model looks at the correctly diseased regions or not, and which kinds of images may be further added to the training dataset to improve the generalization score.

B. Keras + CNN

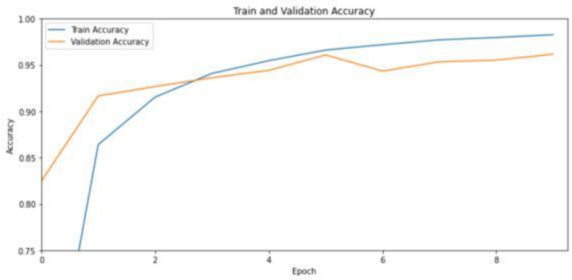

Fig. 8. Train and Validation Accuracy

In the Keras CNN model, a significant achievement is ob-served, with a remarkable accuracy of 96.84%. This indicates that the model is proficient at correctly classifying and recog-nizing patterns in the data. The accuracy is measured along the y-axis, while the x-axis signifies the different training epochs, representing the stages of learning during model training. The blue line, representing the train accuracy, shows that the model is learning and improving with each epoch. Meanwhile, the orange line, representing the validation accuracy, demonstrates that the model maintains a high level of accuracy even when faced with new, unseen data, which is a critical measure of its robustness.

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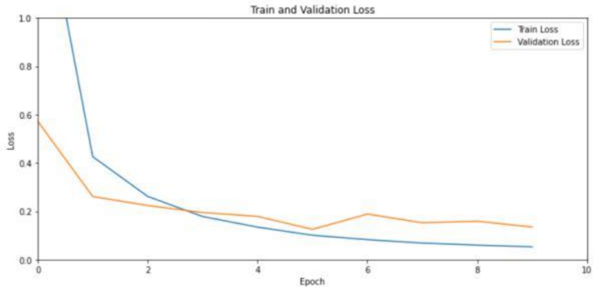

Fig. 9. Train and Validation Loss

Keras+CNN model gives validation loss 1.3 shown in Fig-ures. it gives this result in 10 epochs. More than 3,000 images were given as input to the training model. The trained model is tested on a set of images. Random images are introduced to the network and output label Eventually it is less optimal than the ResNet CNN model. A lower loss is usually better. However, it seems the graph has the labels mixed up, as it says"loss" on the y-axis and epochs on the x-axis.

C. Vgg16

A 92.6% accuracy rate was achieved using early stopping while Training the model on 5 epochs and other side if we look at the loss is 22.6% which is huge than the previous models which shows that it will affeact the accuracy.

Fig. 10. Train and Validation Accuracy in VGG16

Early stopping is a technique where the model is trained for a limited number of training cycles to prevent overfitting. The graph that illustrates this achievement has the y-axis representing accuracy and the x-axis denoting the number of training epochs. In this graph, the green line signifies the training accuracy, showing how well the model is learning on the data it's seen before. Simultaneously, the blue line rep-resents the validation accuracy, indicating how well the model performs on new, unseen data.

This outcome demonstrates that the model is learning efficiently and can make accurate predictions, all within a short training duration, thanks to the smart strategy of early stopping. A loss rate of 22.6% was observed during training, which occurred over a brief period of 5 epochs. The graph illustrates this data, with the y-axis representing accuracy and loss, while the x-axis denotes the number of training epochs.

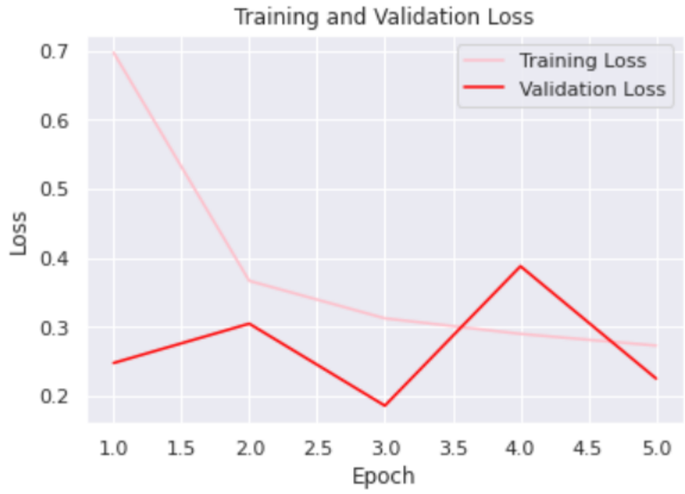

Fig. 11. Train and Validation Accuracy in VGG16

In this visual, the faint red line symbolizes the training loss, indicating how well the model is learning from the known data. Additionally, the solid red line shows the validation loss of the data which we are training in this model. Y axis goes till 1 unit and the X axis goes till 1 to 5 units which shows the no of epochs used for the training and gain the maximum accuracy of the model.

D. Alex Net

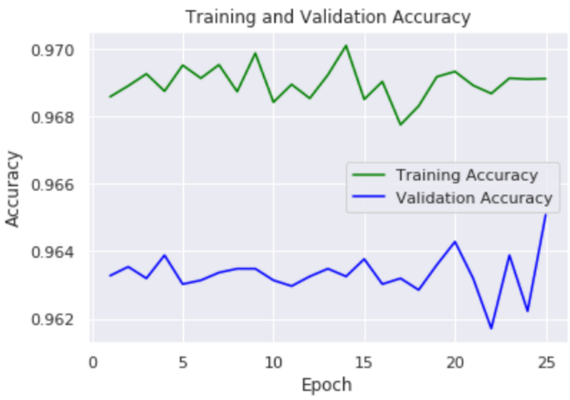

Fig. 12. Training and Validation Accuracy in AlexNet

In the AlexNet model, an impressive training and validation accuracy of 96.78% was achieved, showcasing remarkable consistency with the Keras+CNN model. Both models exhibit strong performance, with accuracy surpassing 90%. The train-ing process extended over 25 epochs, allowing the models to learn from the data thoroughly. The graph, with the y-axis depicting accuracy and loss, and the x-axis indicating the number of training epochs, highlights this achievement. In the graph, the green line represents the training accuracy, illustrating how well the model learns from the data it has seen before. Concurrently, the blue line symbolizes the validation accuracy, revealing the model's proficiency in generalizing to new, unseen data.

Fig. 13. Train and Validation Accuracy in AlexNet

represents the validation loss, which measures how well the model generalizes to new, unseen data.After training the model for 25 epochs, a low loss rate of 9.6% was achieved. The graph indicates this information, with the y-axis showing accuracy and loss, and the x-axis depicting the number of training epochs.

The faint red line reflects the training loss, demonstrating the model's learning from known data, while the solid red line showcases the validation loss, revealing its performance on new, unseen data. The model's relatively low loss rate highlights its ability to learn from training data and maintain good performance on new data.

Accuray and Loss with Various Cnn Mode

In this comparison of different CNN models, the choice of the "better" model depends on the specific needs of the task and the trade-offs between accuracy and training time. ResNet stands out with the highest accuracy of 99.2% and remarkably low loss at 2.6%, achieved in just two training epochs. It excels in scenarios where speed and precision are paramount. AlexNet offers a strong accuracy of 96.78% and a balanced 9.6% loss, though it requires a more extended training duration of 25 epochs, making it suitable for applications with higher accuracy demands but more time for training.

Keras+CNN performs well with a 96.84% accuracy, a slightly higher 13.4% loss, and a reasonable 10-epoch training period, making it a practical and efficient choice for various tasks. VGG16 provides decent accuracy at 92.64% but faces a challenge with a significantly higher loss of 22.51%. However, it requires the shortest training time of just five epochs, offering a speedy solution for specific use cases where time efficiency is critical.

CNN Models	**Accuracy**	**Loss**	**No of Epoches**
ResNet	99.2%	2.6%	2
VGG16	92.64%	22.51%	5
AlexNet	96.78%	9.6%	25
Keras+CNN	96.84%	13.4%	10

Table I Shows Accuracy and Loss of Cnn Models

Ultimately, the selection should align with the specific demands of the application, whether that means prioritizing accuracy or the time available for training

Fig. 14. Res Net Model test on Apple leaf

Res Net Model detect the rust on the apple's leaf and only possible to detect the diseases. When the Res Net model was put to the test on images of apple leaves, it exhibited its proficiency in identifying diseases commonly affecting apple trees, particularly apple cedar and apple rust. With its high accuracy and robust pattern recognition abilities, the model successfully classified these diseases. Apple cedar and apple rust are notorious culprits behind reduced crop yield and quality, making their early detection crucial for effective dis-ease management. Res Net's remarkable accuracy and powerful pattern recognition capabilities have enabled it to excel in the task of distinguishing between these diseases. Its ability to swiftly and accurately identify apple cedar and apple rust provides a valuable tool for apple growers and agriculture experts..
The early detection of apple diseases is of paramount importance, as it empowers farmers to take timely and pre- cise actions, implementing effective treatments and preventive measures. By leveraging the Res Net Model, we not only enhance our ability to protect apple trees from these destructive diseases but also ensure better crop yields and the preservation of orchard health. This technological advancement holds the potential to revolutionize the way we manage apple orchards, ultimately contributing to a more sustainable and productive agriculture industry.
In the future, this model's success in disease detection opens up possibilities for the development of automated systems that can monitor orchards continuously. These systems can provide real-time information on disease outbreaks, enabling even more proactive and precise management of apple orchards. This holistic approach, combining disease detection and pre-vention, offers promise for a brighter and more prosperous future for apple cultivation.

5. CONCLUSION AND FUTURE WORK

After getting the optimal validation scores for VGG16, Res Net, Keras+ CNN and Alexnet, we conclude that the ResNet model performs the best of all. shows the accuracy comparison for the four models, where this is apparent. We also plot accuracy and loss curves for the three models. From the accuracy curves, we observe that keras+CNN model and AlexNet model reaches the highest score very soon, compared to the other two models.VGG is a smaller model, which could be why it fails to learn the data well and does no perform as well as the other three models.
Our model performs well only on the images which are from the classes the model already knows. It will not be able to detect the correct class for any out-of-domain data. This problem needs to be addressed in the future.
In addition to detection, we aim to further support farmers and growers by providing remedies and precautions to combat the identified diseases effectively. This holistic approach not only helps in diagnosis but also offers actionable solutions for disease management. By integrating

this feature into our system, we can empower agriculture communities with the knowledge and tools they need to address plant diseases promptly and efficiently, ultimately contributing to improved crop health and agricultural sustainability. This work sets a strong foundation for a more comprehensive and impactful tool for the agricultural shave been working on precautions and remedies will also give along with the desease detection.

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