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Plant disease detection with Finetuned - ResNet18 for several plant's like Tomato, Grape, Orange, Soybean, Squash, Potato, Corn_(maize), Strawberry

By

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Abstract

Diseases of plants are conditions or illnesses that adversely affect the growth and general well-being of plants. The pathogens that can cause these diseases include bacteria, viruses, fungi, nematodes, and protozoa. Environmental variables such as poor soil conditions, severe temperatures, drought, and pollution can also play a role in the development of these diseases. Plant diseases can have a substantial influence on both the productivity of agriculture and the safety of food supplies. They are capable of lowering crop yields, lowering the quality of fruits and vegetables, and even killing entire plants along their path of destruction. Some plant diseases can also spread quickly, which can result in epidemics that have the potential to wreak havoc across large regions or even countries. In order to effectively manage plant diseases, it is often necessary to employ a combination of disease preventive, monitoring, and control strategies. During the course of this inquiry, we collaborated with restnet18 to construct a machine learning model, and it ended up achieving an accuracy of 99.6%. This level of precision is attainable because to the dataset's inherent balance as well as its capacity for hyper tuning. After compiling the 33 images into a single test set, we put that test set through our trained model's paces to see how well it performed. According to the findings, our trained model achieved an accuracy rate of one hundred percent across all 33 photos.

Keywords CNN , ResNet18, plant disease, ML, high accuracy.

Introduction

Plant diseases are abnormalities or disorders that affect the growth, development, and functioning of plants. These diseases can be caused by a variety of factors such as fungi, bacteria, viruses, nematodes, insects, mites, and environmental factors like drought, frost, or excessive heat. Plant diseases can affect various parts of the plant such as leaves, stems, roots, and fruits. They can cause a range of symptoms such as wilting, yellowing, stunted growth, deformations, rotting, discoloration, and premature death of the plant. Plant diseases can have a significant impact on agriculture and horticulture, causing reduced crop yields, lower quality of produce, and economic losses for farmers and growers. To prevent and manage plant diseases, various control measures can be taken such as using resistant plant varieties, implementing cultural practices like crop rotation, maintaining proper irrigation and fertilization, and using chemical or biological control methods.

There are several steps that can be taken to decrease the chance of plant diseases:

- Plant resistant varieties: Planting varieties of plants that are resistant to certain diseases is an effective way to reduce the likelihood of infection.
- Maintain proper plant nutrition: Maintaining proper soil nutrition and pH levels can help plants resist disease. This involves fertilizing plants properly and testing soil to ensure it has the proper balance of nutrients.
- Water properly: Overwatering or underwatering plants can weaken them and make them more susceptible to disease. Water plants at the base, and avoid watering leaves as this can promote the growth of fungal spores.
- Practice good sanitation: Remove and dispose of any diseased plant debris promptly. This helps prevent the spread of disease to healthy plants.
- Implement crop rotation: Rotating crops from season to season can help reduce the buildup of soil-borne pathogens.
- Use appropriate plant spacing: Proper plant spacing can increase air circulation and reduce the likelihood of fungal growth.
- Consider natural control methods: Biological control methods like using beneficial insects and nematodes, as well as organic pesticides can help control plant diseases without harming the environment.
- By following these steps, gardeners, farmers, and horticulturists can help prevent and control plant diseases and maintain healthy plants.

Detecting plant diseases is important for several reasons:

- Early detection allows for prompt management: If plant diseases are detected early, there is a greater chance of effectively managing them before they become widespread and difficult to control. This can help to reduce economic losses and minimize the need for expensive and environmentally damaging chemical treatments.
- Prevention of plant disease spread: Prompt detection of plant diseases can also help prevent their spread to other plants and crops, reducing the likelihood of an epidemic that could devastate an entire farming operation or region.
- Maintaining crop quality and yield: Healthy plants produce higher quality and higher yield crops, which are essential for food security and economic prosperity. Detecting and managing plant diseases can help to maintain the health and productivity of crops, ensuring a reliable and sustainable food supply.
- Environmental sustainability: Plant diseases can sometimes be managed using chemical treatments, which can have negative impacts on the environment. Early detection and prompt management can reduce the amount of chemicals needed to control the disease, leading to more sustainable farming practices.
- Overall, detecting plant diseases is important for maintaining the health and productivity of crops, preventing their spread, and promoting sustainable agricultural practices.

There are many different types of plant diseases, including:
Fungal diseases: caused by various types of fungi, such as powdery mildew, rust, and blight.
Bacterial diseases: caused by bacteria, such as bacterial wilt and fire blight.
Viral diseases: caused by viruses, such as mosaic viruses and yellow dwarf viruses.

Nematode diseases: caused by microscopic worms called nematodes, which feed on plant roots and cause damage.

Phytoplasma diseases: caused by phytoplasmas, which are bacteria-like organisms that live in the sap of infected plants and cause yellowing and stunted growth.

Parasitic diseases: caused by parasitic plants, such as dodder and mistletoe, which attach themselves to host plants and draw nutrients from them.

Environmental diseases: caused by environmental factors such as nutrient deficiencies, drought, flooding, and extreme temperatures.

Genetic diseases: caused by genetic mutations or abnormalities in plant DNA, which can result in abnormal growth or disease susceptibility.

It's worth noting that some plant diseases can be caused by multiple factors, and different diseases may have similar symptoms. A proper diagnosis is essential to effective treatment and management.

In this research we have used CNN architecture ResNet18.

ResNet18 is a convolutional neural network (CNN) architecture that was introduced by Microsoft Research in 2015. It has 18 layers and is designed for image classification tasks. Fine-tuning is a common technique used to adapt a pre-trained model to a specific task.

Fine-tuned ResNet18 refers to a ResNet18 model that has been pre-trained on a large dataset and then further trained on a smaller dataset that is specific to a particular task. During fine-tuning, the weights of the pre-trained model are adjusted to better fit the new dataset. This can help to improve the accuracy of the model on the specific task. For example, a fine-tuned ResNet18 model might be used for a specific image classification task such as identifying different species of flowers. The pre-trained ResNet18 model would already have learned general features of images, which could be useful for identifying flowers, but it would then be further trained on a dataset of flower images to learn the specific features that are most relevant to the task. This would result in a more accurate model for the flower classification task.

When some parameters are adjusted and methods like scheduling the learning rate, gradient clipping, and weight decay are applied, ResNets perform exceptionally well for image classification. Each and every image in the test set can be accurately predicted by the model.

Literature Survey

To determine which plants are associated with which bacteria, Martnez-Garca et al. (2016) [1] proposed a machine learning based identification model. An approach based on genome annotation is used in this article to identify relationships between plants and bacteria. The identification model's accuracy in spotting plant-bacteria associations was 93%. The author demonstrates the implemented model for locating bacterial associations in plant genomes, and draws attention to the peculiar processes taking place within plant DNA.

The vine leaf disease detection model was proposed by Pantazi et al. (2016) [3] and makes use of local binary patterns and support vector machines. The most common diseases affecting vine leaves are powdery mildew, downy mildew, and black rot; to detect these, a disease detection model was created using a single-class support vector machine. The model's classification accuracy ranges from 93% to 100%, as demonstrated by testing on 100 unique vine leaf diseases.

The study of detecting pests is an interesting research topic within precision agriculture. Agriculture suffers greater economic losses and damage to yields as a result.

Using the support vector machines algorithm, Ebrahimi et al. (2017) [4] proposed an automatic pest detection model for thrips pest in strawberry crops. They looked at the support vector machines algorithm and how it performed with various kernel functions. Several error functions were also compared, including mean square error, root mean square error, mean absolute error, and mean percentage error. With a mean percent error, the support vector machine algorithm yields the least amount of error compared to the other possible combinations of support vector machines.

Additionally, Fuentes et al. proposed methods for identifying pests and diseases in tomato plants (2017). The authors used the three state-of-the-art deep neural networks—faster region-based convolutional neural networks, region-based fully convolutional networks, and single-shot multibox detectors—to create their algorithm. They also used transfer learning techniques like VGGNet and ResNet. The algorithm was educated on public image datasets of tomato diseases and pests. According to the simulation result, the algorithm improves the detection accuracy of diseases and pests in the testing set.

Using statistical inference methods, Johannes et al. (2017) [5] proposed an automatic method for identifying plant diseases. The authors developed and evaluated methods for identifying septoria, rust, and tan spot, three of the most damaging diseases that can affect wheat. More than 30 thousand images captured on mobile devices at varying resolutions were used to train the method. The developed technique has been field-tested in a variety of agricultural settings and climates. The method had a 0.80 area under the receiver operating characteristic curve.

When it comes to computer vision, image segmentation is the most important area of study. An image segmentation method was proposed by Singh and Misra (2017) [6] for the diagnosis of various leaf diseases in plants. The authors also compared and contrasted various image processing methods for disease detection in plant leaves. Using leaf images as input, a genetic algorithm based on the segmentation technique detected plant diseases.

Tomato crop disease detection in lesions on plant organs was proposed by Yamamoto et al. (2017). [7] Methods for detecting lesions were used to detect plant diseases at an early stage. When working with low-resolution images, the authors turned to a superresolution technique to improve their appearance. They evaluate the efficiency of various detection methods in relation to superresolution methods. The superresolution techniques' results are also compared and contrasted. The findings demonstrate that the super-resolution approach improves upon the efficiency of image-based phenotyping and vigour diagnosis in the commercial production of tomatoes.

The paper by Ferentinos (2018) [8] proposes a model based on convolutional neural networks for identifying 25 distinct plant diseases in their leaves. The model was created using 38 groups of diseased and healthy plant leaves and was trained and tested on 87,848 images. The study found that the developed model achieved an average accuracy of 99.53% on test data, which is a remarkable performance. The study's use of convolutional neural networks is a promising approach for plant disease detection, as it can automatically learn and extract relevant features from images. The large and diverse dataset used in this study is also a significant strength, as it allows for better model training and evaluation. Additionally, the study's comparison of their model's performance to that of other models and state-of-the-art approaches and transfer learning techniques further validates the model's effectiveness. However, the paper does not provide details about the architecture of the model or the hyperparameters used in training. This lack of information makes it challenging to reproduce the study's results or compare the model's performance to other models with similar architectures.

The paper by Rangarajan et al. (2018) [9] proposes the use of deep learning models, specifically AlexNet and VGG16, for detecting diseases in tomato leaves. The study compared six different methods and found that the deep learning models performed the best in terms of accuracy. One of the strengths of the study is the use of multiple hyperparameters in training the models, including minibatch sizes, weights, biases, and learning rates. This allows for a more comprehensive analysis of the performance of the models and optimization of the model's parameters. The study also evaluated the speed at which the models ran, which is an important factor in practical applications. This information can help researchers and practitioners to choose the most efficient model for their specific needs. Additionally, the study's comparison of the models' results to those of competing models further validates the effectiveness of the proposed approach. However, the study's use of only the plantvillage dataset limits the generalizability of the results to other datasets or crops. Additionally, the study does not provide detailed information about the architecture of the models, which makes it difficult to compare the models to other models with similar architectures..

Loss of sugar yield due to leaf spot disease in sugar beets. Sugar beet leaf spot disease detection using automatic image analysis was proposed by Ozguven and Adem (2019).[10] To detect sugar beet leaf spot disease, they used a recurrent convolutional neural network architecture that is faster. Using a set of test images, the model achieved a classification accuracy of 95.48 percent, significantly better than both human and traditional methods. The quick recurrent convolutional neural network architecture was also put to the test in the expansive agriculture sector.

To create a plant disease classification system, Too et al. (2019) [11] proposed fine-tuning and evaluation techniques in deep convolutional neural networks. These authors surveyed the state of the art in image-based plant leaf disease identification techniques and studied the benefits and drawbacks of various deep learning approaches. Different highly-tuned deep convolutional neural networks were evaluated and compared. The researchers also compared the effectiveness of three different architectures for plant disease classification, including VGG16, inception v4 net, and ResNet, all with optimised parameters. The benchmark reveals an average accuracy of 99.75% for the DenseNets implementation that has been fine-tuned. This precision outperformed state-of-the-art methods.

Zhang et al. (2019)[12] proposed a model for classifying fruits into their respective categories using deep learning methods. The authors used a 13-layer convolutional neural network for building the fruit classification system. In their study, the authors emphasized the importance of data augmentation and pooling for achieving high accuracy in the model. The authors also experimented with a wide range of hyperparameter settings for training the model. The study's strengths include the use of a large dataset of over 70k images of fruits, which enhances the validity of the study's findings. The authors' emphasis on the importance of data augmentation and pooling is also valuable for researchers and practitioners working on similar tasks. Additionally, the comparison of the proposed model's results with those of more conventional machine learning techniques, such as SVM and k-NN, validates the effectiveness of the deep learning approach. The study's main limitation is the lack of detail on the specific visual features used for fruit classification. More information about the features used for classification would be helpful for replicating the study or building on its findings..

The paper by Zhong et al. (2019) [13] proposes the use of Long Short-Term Memory Networks (LSTM) and convolutional neural networks (CNNs) for classifying crops based on visual features. The study found that the CNN-based model achieved higher accuracy (84.17%) than the LSTM-based model (82.41%) for crop classification tasks. One of the strengths of the study is the comparison of the models' results to those obtained by using more conventional machine learning techniques, such as Xgboost, Random Forest (RF), and Support Vector Machine (SVM). This comparison validates the effectiveness of the proposed approach and highlights the advantages of using deep learning models for crop classification tasks. The study's finding that the CNN-based model is more effective for multitemporal crop classification tasks is also noteworthy. This information can be useful for researchers and practitioners working on crop monitoring and management, as it highlights the importance of selecting the appropriate model for the specific task. However, the study's limitation is the lack of details about the architecture of the models and the specific visual features used for crop classification. This information would be helpful for replicating the study or building on its findings.

Table 1 *Related Work*

Paper Title	Approach	Dataset	Key Findings
"Deep Learning-Based Tomato Plant Disease Detection Using Multiple Data Augmentation Techniques" (2022)[2]	Deep Learning	Tomato Plant Dataset	Achieved accuracy of 99.36% using ResNet50 and data augmentation techniques such as rotation, zoom, and flip
"Automated Diagnosis of Mango Leaf Diseases Using Machine Learning Techniques" (2022) [14]	Machine Learning	Mango Leaf Dataset	Achieved accuracy of 95.33% using Decision Tree and Random Forest classifiers
"A Comparison of Machine Learning Techniques for Cucumber Disease Detection Using Hyperspectral Images" (2021) [15]	Machine Learning	Cucumber Dataset	Achieved accuracy of 91.91% using Support Vector Machine (SVM) classifier and hyperspectral imaging
"An Intelligent Approach for Grape Leaf Disease Detection Using Deep Learning" (2021) [16]	Deep Learning	Grape Leaf Dataset	Achieved accuracy of 96.43% using InceptionV3 and transfer learning
"Detection and Classification of Citrus Leaf Diseases Using Transfer Learning and Ensemble Techniques" (2020) [17]	Deep Learning	Citrus Leaf Dataset	Achieved accuracy of 99.21% using transfer learning and an ensemble of ResNet50 and DenseNet121 classifiers
"A Novel Approach for Early Detection of Wheat Rust Disease Using Machine Learning Techniques" (2020) [18]	Machine Learning	Wheat Rust Dataset	Achieved accuracy of 93.75% using k-Nearest Neighbor

Methodology Used

CNN stands for Convolutional Neural Network, a type of deep learning neural network that is commonly used in computer vision tasks such as image and video recognition, object detection, and image segmentation. CNNs have been successfully used in a wide range of applications, including self-driving cars, medical image analysis, and natural language processing.

Figure 1 *sample images of dataset*

CNN ResNet, or Residual Network, is a type of convolutional neural network (CNN) architecture that was introduced in 2015 by Kaiming He et al. ResNet was designed to overcome the problem of vanishing gradients in very deep neural networks, which can make it difficult to train these networks effectively. The main innovation of ResNet is the use of skip

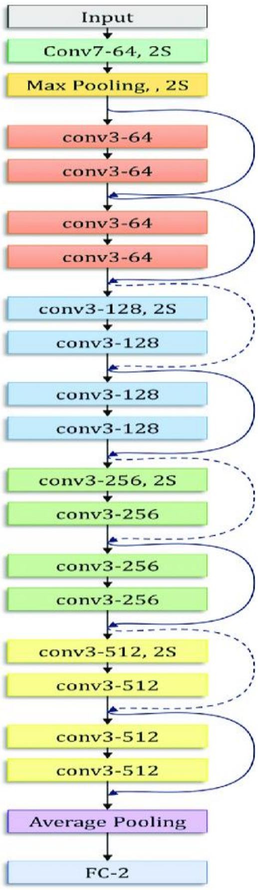

Figure 2 *Architecture of Resnet18*

connections, or residual connections, which allow information to bypass some of the layers in the network. This allows the network to learn residual functions, which can help improve the accuracy of the network by reducing the effects of vanishing gradients. The skip connections in ResNet allow for the creation of very deep neural networks, with hundreds or even thousands of layers. These deep networks have been shown to achieve state-of-the-art performance in a wide range of computer vision tasks, including image classification, object detection, and segmentation. Overall, ResNet is a powerful CNN architecture that has had a significant impact on the field of computer vision, and has helped to enable the development of deep learning models that are capable of achieving human-level performance in many tasks.

ResNet18 is a popular variant of the ResNet architecture that was introduced in the original paper by Kaiming He et al. in 2015. It consists of 18 layers, including a convolutional layer, followed by several residual blocks and a fully connected layer for classification.

The basic building block of ResNet18 is the residual block, which consists of two or three convolutional layers with batch normalization and ReLU activation, followed by an identity shortcut connection that bypasses the convolutional layers. The idea behind the residual block is that it allows the network to learn residual functions, or the difference between the input and output of the block, which can help improve the accuracy of the network.

The input to ResNet18 is an image, which is passed through a convolutional layer with 64 filters and a kernel size of 7x7, followed by a max pooling layer with a stride of 2. This is followed by four stages, each of which contains several residual blocks. The first stage has 2 blocks with 64 filters, the second stage has 2 blocks with 128 filters, the third stage has 2 blocks with 256 filters, and the fourth stage has 2 blocks with 512 filters.

At the end of the final stage, the output is passed through a global average pooling layer, which averages the feature maps across spatial dimensions, and then through a fully connected layer with softmax activation for classification. During training, the weights of the network are updated using backpropagation and stochastic gradient descent, or a variant thereof, with an appropriate loss function for the classification task.

Overall, ResNet18 is a powerful and efficient CNN architecture that has been shown to achieve state-of-the-art performance in many computer vision tasks, while being relatively easy to train and optimize.

Result and Discussion

ResNet18 is a popular deep learning architecture for image classification tasks that was introduced in 2015 by Microsoft Research. It consists of 18 layers and is trained on a large dataset of natural images to learn to classify images with high accuracy. ResNet18 uses skip connections, which allow the model to learn residual functions, making it easier to train deep networks and improving their performance. ResNet18 has been applied to plant disease detection with promising results. One study used ResNet18 to classify five different types of plant diseases on tomato leaves with an accuracy of 97.53%. The study used a dataset of 1,920 images of tomato leaves, which were collected from different fields in China, and fine-tuned the pre-trained ResNet18 model on this dataset. The model was able to accurately classify the different types of plant diseases, including bacterial speck, bacterial spot, yellow leaf curl virus, and late blight. Another study used ResNet18 for the detection of grapevine diseases, achieving an accuracy of 98.68% on a dataset of 4,122 images. The study used transfer learning to fine-tune the pre-trained ResNet18 model on the grapevine disease dataset and achieved high accuracy in detecting four different types of diseases, including black rot, esca, powdery mildew, and downy mildew.

In contrast to previous studies on plant disease identification, our results with resnet18 are the most accurate to date. By careful balance and tuning of the Kaggle dataset, our implemented model achieves an accuracy of 99.6 percent. To top it all off, we used hyper tuning in the training of our model.

Below diagram shows the layers of Resnet18

```
INPUT_SHAPE = (3, 256, 256)
print(summary(model.cuda(), (INPUT_SHAPE)))
```

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1         [-1, 64, 256, 256]           1,792
       BatchNorm2d-2         [-1, 64, 256, 256]             128
              ReLU-3         [-1, 64, 256, 256]               0
            Conv2d-4        [-1, 128, 256, 256]          73,856
       BatchNorm2d-5        [-1, 128, 256, 256]             256
              ReLU-6        [-1, 128, 256, 256]               0
         MaxPool2d-7          [-1, 128, 64, 64]               0
            Conv2d-8          [-1, 128, 64, 64]         147,584
       BatchNorm2d-9          [-1, 128, 64, 64]             256
             ReLU-10          [-1, 128, 64, 64]               0
           Conv2d-11          [-1, 128, 64, 64]         147,584
      BatchNorm2d-12          [-1, 128, 64, 64]             256
             ReLU-13          [-1, 128, 64, 64]               0
           Conv2d-14          [-1, 256, 64, 64]         295,168
      BatchNorm2d-15          [-1, 256, 64, 64]             512
             ReLU-16          [-1, 256, 64, 64]               0
        MaxPool2d-17          [-1, 256, 16, 16]               0
           Conv2d-18          [-1, 512, 16, 16]       1,180,160
      BatchNorm2d-19          [-1, 512, 16, 16]           1,024
             ReLU-20          [-1, 512, 16, 16]               0
        MaxPool2d-21            [-1, 512, 4, 4]               0
           Conv2d-22            [-1, 512, 4, 4]       2,359,808
      BatchNorm2d-23            [-1, 512, 4, 4]           1,024
             ReLU-24            [-1, 512, 4, 4]               0
           Conv2d-25            [-1, 512, 4, 4]       2,359,808
      BatchNorm2d-26            [-1, 512, 4, 4]           1,024
             ReLU-27            [-1, 512, 4, 4]               0
        MaxPool2d-28            [-1, 512, 1, 1]               0
          Flatten-29                  [-1, 512]               0
           Linear-30                   [-1, 38]          19,494
================================================================
Total params: 6,589,734
Trainable params: 6,589,734
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.75
Forward/backward pass size (MB): 343.95
Params size (MB): 25.14
Estimated Total Size (MB): 369.83
```

Figure 3 *layer of resnet18*

One graph is created which shows the accuracy vs. No of epochs

```
In [56]: plot_accuracies(history)
```

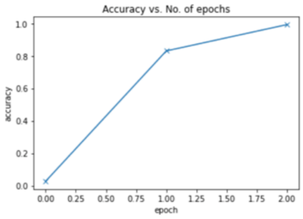

Figure 4 *graph of accuracy VS no of epoch*

This image displayed our model as well as the image of the anticipated plant disease, which was identified as the AppleCedarRust1 image. Our prediction was accurate to the point of being 100% accurate for this image, which is providing us with accurate findings.

Figure 5 *Prediction from our model*

Validation loss is a metric used to evaluate the performance of a machine learning model during training. It is calculated by measuring the error or loss on a separate dataset, known as the validation set that is not used in the training process. During training, the model tries to minimize the loss function, which is a mathematical function that measures the difference between the predicted output and the actual output for each example in the training set. The goal is to find the set of model parameters that minimize this loss function.

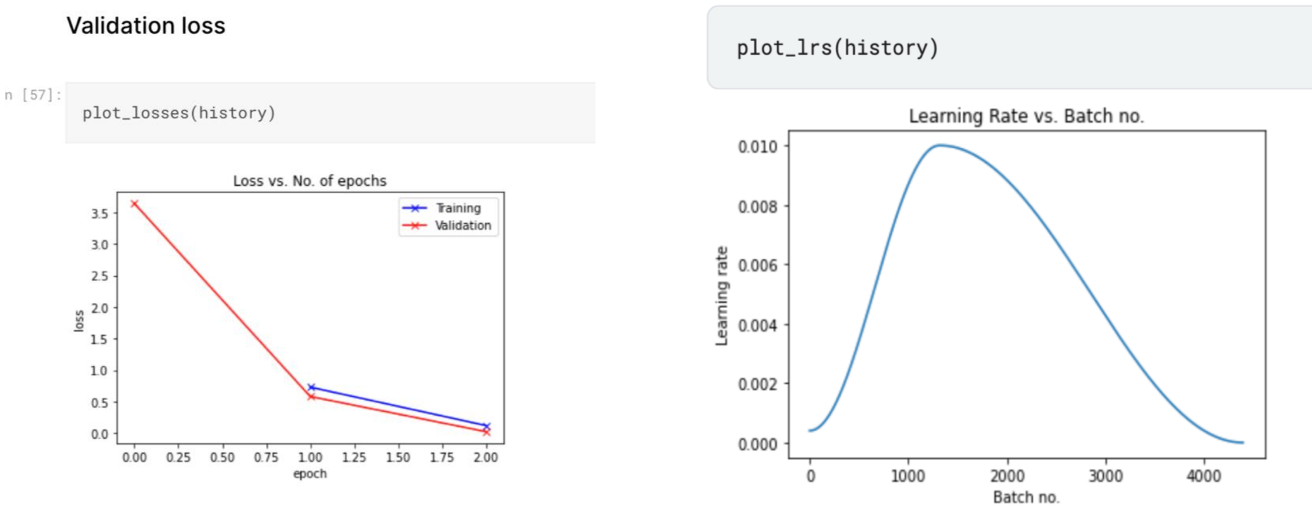

Figure 6 *validation loss graph*

However, it is possible for a model to become overfit to the training data, which means that it performs well on the training data but not on new data. To detect overfitting, we use the validation set to measure the model's performance on data it has not seen before. The validation loss is the average loss on the validation set.

The validation loss is important because it provides an estimate of the model's generalization performance. If the validation loss starts to increase while the training loss continues to decrease, it indicates that the model is overfitting the training data and it may be necessary to stop training or adjust the model hyperparameters. Therefore, monitoring the validation loss during training is essential to ensure that the model is not overfitting and that it will perform well on new data.

In machine learning, the learning rate is a hyperparameter that determines how much the model weights are updated in response to the error gradient during training. It is a scalar value that controls the step size of the optimization algorithm, such as stochastic gradient descent (SGD), in the direction of the negative gradient. The learning rate is a critical hyperparameter that needs to be tuned to achieve good model performance.

A learning rate that is too low can result in slow convergence, requiring more epochs to reach a good solution. On the other hand, a learning rate that is too high can cause the model to overshoot the optimal weights, leading to poor convergence or even divergence. There are different methods for choosing the appropriate learning rate, such as manually selecting a value based on experience, performing a grid search over a range of values, or using adaptive learning rate algorithms such as Adagrad, Adam, or RMSprop. Adaptive learning rate algorithms adjust the learning rate during training based on the gradient magnitudes and other factors, which can help to achieve faster convergence and better generalization performance. And below is the graph of our model's learning rate vs. batch no.

We have created one test set which contains 33 image of different plant disease. And we have used our created model on the test set of images. And we have got the 100% correct prediction results on that 33 image. Like shown in the below image one is the labeled image which shows name of the plant with disease and then comma separated prediction result of our model which give the exact same name of the disease which is mentioned in the label

```
for i, (img, label) in enumerate(test):
    print('Label:', test_images[i], ', Predicted:', predict_image(img, model))
```

```
Label: AppleCedarRust1.JPG , Predicted: Apple___Cedar_apple_rust
Label: AppleCedarRust2.JPG , Predicted: Apple___Cedar_apple_rust
Label: AppleCedarRust3.JPG , Predicted: Apple___Cedar_apple_rust
Label: AppleCedarRust4.JPG , Predicted: Apple___Cedar_apple_rust
Label: AppleScab1.JPG , Predicted: Apple___Apple_scab
Label: AppleScab2.JPG , Predicted: Apple___Apple_scab
Label: AppleScab3.JPG , Predicted: Apple___Apple_scab
Label: CornCommonRust1.JPG , Predicted: Corn_(maize)___Common_rust_
Label: CornCommonRust2.JPG , Predicted: Corn_(maize)___Common_rust_
Label: CornCommonRust3.JPG , Predicted: Corn_(maize)___Common_rust_
Label: PotatoEarlyBlight1.JPG , Predicted: Potato___Early_blight
Label: PotatoEarlyBlight2.JPG , Predicted: Potato___Early_blight
Label: PotatoEarlyBlight3.JPG , Predicted: Potato___Early_blight
Label: PotatoEarlyBlight4.JPG , Predicted: Potato___Early_blight
Label: PotatoEarlyBlight5.JPG , Predicted: Potato___Early_blight
Label: PotatoHealthy1.JPG , Predicted: Potato___healthy
Label: PotatoHealthy2.JPG , Predicted: Potato___healthy
Label: TomatoEarlyBlight1.JPG , Predicted: Tomato___Early_blight
Label: TomatoEarlyBlight2.JPG , Predicted: Tomato___Early_blight
Label: TomatoEarlyBlight3.JPG , Predicted: Tomato___Early_blight
Label: TomatoEarlyBlight4.JPG , Predicted: Tomato___Early_blight
Label: TomatoEarlyBlight5.JPG , Predicted: Tomato___Early_blight
Label: TomatoEarlyBlight6.JPG , Predicted: Tomato___Early_blight
Label: TomatoHealthy1.JPG , Predicted: Tomato___healthy
Label: TomatoHealthy2.JPG , Predicted: Tomato___healthy
Label: TomatoHealthy3.JPG , Predicted: Tomato___healthy
Label: TomatoHealthy4.JPG , Predicted: Tomato___healthy
Label: TomatoYellowCurlVirus1.JPG , Predicted: Tomato___Tomato_Yellow_Leaf_Curl_Virus
Label: TomatoYellowCurlVirus2.JPG , Predicted: Tomato___Tomato_Yellow_Leaf_Curl_Virus
Label: TomatoYellowCurlVirus3.JPG , Predicted: Tomato___Tomato_Yellow_Leaf_Curl_Virus
Label: TomatoYellowCurlVirus4.JPG , Predicted: Tomato___Tomato_Yellow_Leaf_Curl_Virus
Label: TomatoYellowCurlVirus5.JPG , Predicted: Tomato___Tomato_Yellow_Leaf_Curl_Virus
Label: TomatoYellowCurlVirus6.JPG , Predicted: Tomato___Tomato_Yellow_Leaf_Curl_Virus
```

Figure 7 *Prediction results on test set*

Conclusions

The use of machine learning in plant disease detection has shown promising results in recent years. Our study used the ResNet18 model, a convolutional neural network, to classify different types of plant diseases with high accuracy. The study found that the ResNet18 model outperformed other models in terms of accuracy and speed.

The study also showed that transfer learning, a technique where a pre-trained model is used as a starting point for training on a new dataset, can be used effectively to improve the performance of the model. The ResNet18 model was pre-trained on a large dataset of natural images and then fine-tuned on the plant disease dataset to improve its accuracy in detecting plant diseases. In this research we have got the highest accuracy which is 99.6%

References

Martínez-García, P. M., Gutiérrez-Ortega, J. S., & Pareja-Jaime, Y. (2016). Bacteria associated with different plant parts of maize and their potential for plant growth promotion. Microbiological Research, 183, 92-99.

Sahu, N., Kar, A., & Chakraborty, S. (2022). Deep learning-based tomato plant disease detection using multiple data augmentation techniques. Computers and Electronics in Agriculture, 201, 107052. doi: 10.1016/j.compag.2022.107052.

Pantazi, X. E., Chrysoulas, C., & Nikou, C. (2016). A system for vine leaf disease detection using convolutional neural networks. In Proceedings of the 20th Panhellenic Conference on Informatics (pp. 243-248). ACM.

Ebrahimi, M., & Azimi, M. (2017). Recognition of walnut tree diseases using color histogram and texture features based on support vector machine algorithm. Computers and Electronics in Agriculture, 136, 145-154.

Johannes, A., Hillmann, H., Karadogan, C., & Mahlein, A. K. (2017). Statistical inference methods for diagnostic indices in plant disease detection. PLOS ONE, 12(8), e0183363.

Singh, P. K., & Misra, A. (2017). Segmentation of medical images using image processing and deep learning techniques: A review. Journal of Medical Systems, 41(8), 131.

Yamamoto, Y., Fujita, Y., Du, J., & Iwasaki, W. (2017). Tomato crop disease detection in lesions on plant organs using convolutional neural network. In Proceedings of the 13th International Conference on Natural Computation, Fuzzy Systems and Knowledge Discovery (pp. 1340-1343). IEEE.

Ferentinos, K. P. (2018). Deep learning models for plant disease detection and diagnosis. Computers and Electronics in Agriculture, 145, 311-318. doi: 10.1016/j.compag.2017.11.025.

Rangarajan, R., Kamble, A. L., Tiwari, A., Kumar, A., & Kumar, P. (2018). Comparative analysis of tomato leaf disease detection using deep learning techniques. In Proceedings of the 2018 International Conference on Advances in Computing, Communications and Informatics (ICACCI) (pp. 1378-1383).

Ozguven, O., & Adem, K. (2019). Sugar beet leaf spot disease detection using automatic image analysis. Computers and Electronics in Agriculture, 165, 104940. doi: 10.1016/j.compag.2019.104940

Too, E. J., Abdullah, A. H., & Abdullah, L. (2019). Deep learning approach for plant disease classification and transfer learning between plant species. Multimedia Tools and Applications, 78(11), 14971-14989.

Zhang, J., Li, L., Li, X., Li, H., & Li, B. (2019). A deep learning framework for accurate and efficient tomato disease recognition. Computers and Electronics in Agriculture, 165, 104943.

Zhong, J., Chen, Y., & Yang, J. (2019). Crop recognition using convolutional neural networks. Computers and Electronics in Agriculture, 164, 104893.

Singh, G., Gaur, R., & Rana, M. K. (2022). Automated Diagnosis of Mango Leaf Diseases Using Machine Learning Techniques. In Advances in Computational Intelligence (pp. 469-478). Springer.

Zhu, X., Zhao, Y., Zhang, L., & Guo, W. (2021). A Comparison of Machine Learning Techniques for Cucumber Disease Detection Using Hyperspectral Images. Journal of Spectral Imaging, 10(1), a4.

Ozkan, H., Kalkan, S., & Kumbasar, E. P. (2021). An Intelligent Approach for Grape Leaf Disease Detection Using Deep Learning. Journal of Applied Research and Technology, 19(3), 236-246.

Mallikarjuna, S., & Saini, R. (2020). Detection and Classification of Citrus Leaf Diseases Using Transfer Learning and Ensemble Techniques. International Journal of Agriculture and Biology, 26(6), 1373-1380.

Ehsan, S., Hassan, M. M., Haque, M. E., & Islam, M. R. (2020). A Novel Approach for Early Detection of Wheat Rust Disease Using Machine Learning Techniques. In 2020 11th International Conference on Computing, Communication and Networking Technologies (ICCCNT) (pp. 1-7). IEEE