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Disease Detection and Diagnosis of Agricultural Plant Leaf Using Machine Learning

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ABSTRACT- Agriculture and allied activities still continue to be one of the major occupations in world. Various modern methods and inventions have been incorporated to make it more efficient and successful. One of the main problems the farmers are facing are plant diseases. This can affect the entire yield of a season, so to tackle that problem we are proposing a ResNet based Convolutional neural network model which can detect the various disease in plants in early stage itself. For this purpose, 'New plant village' dataset to train and test the model. The proposed Resnet based approach has achieved high accuracy in detecting diseases as well as suggesting a proper solution and possible causes for a plant disease.

Keywords: ResNet, CNN, Plant Disease, Accuracy.

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1. INTRODUCTION

Human race has been practising the art of growing plants for centuries. Agriculture is still one of the major occupations followed in India. Major part of the labour force is employed into agriculture and its allied activities. Food is one of the basic necessities for survival of people. Various issues arise related to agriculture and consumption of food all around the world. Food security is one of the major problems faced throughout the world, so it is necessary to ensure sustainable crop management techniques are being followed.

The crop growing technique which was followed a century back is not practised anymore. Modern technological advancements are incorporated to make the it more efficient. With the help of growth in technology various improvements have been widely implemented and produces fruitful result. The world is changing due to various natural and human made phenomenon, many new problems arise which has direct effect in the field of agriculture. One of the major problems that affects the yield is plant diseases. The microorganisms which infect the plants are getting more immune to pesticides, it is of much need for disease detection at primary stage. More and more pathogens infect plants on a larger scale and it is getting difficult to control its growth.

This issue can be solved with the help of modern scientific methods. One such way is to use machine learning models to predict the type of disease which affected the plant. Upon time it has been proved that machine learning to be widely efficient in solving various issues including in the field of agriculture. Various models have been developed like Alexnet, Googlenet, VGG etc as an extension for convolutional neural network (CNN). With advancements in photo capturing techniques images can be obtained in the required specification which can help the machine learning models to predict and classify the necessary data in an easier fashion.

The authors [3] applied the basic concept of isolation by first localized the affected part of the plant leaf using random sample consensus (RANSAC). They pre-processed the input image and initialized seed points before performing boundary extraction. This resulted in a localized image from which classification was done, achieving an accuracy of 93% through the use of additional algorithms such as logistic regression and multiplayer perception model.

The study by [8] employed multiple models, including random forest, SVM, and KNN, to detect plant disease. The highest accuracy of 87.43% was achieved using the random forest model, which utilized 250 estimators. In the KNN model, a value of k = 5 was used to prevent single point predictions. The authors also used various features, such as entropy, contrast, and correlation, for classification.

The originators [12] have utilized a combination of a convolutional neural network (CNN) and learning vector

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quantization (LVQ) to classify images. 400 training and 100 testing images were used, and three matrices were generated for three colors. A Kohonen layer with 50 neurons was also incorporated. The LVQ method combines competitive learning and supervised learning, utilizing reference vectors to identify classes and adjust weights during training. Additionally, filters were applied to the RGB channels. This approach resulted in an accuracy of 86%.

The authors [13] have applied a KNN method where the images are analyzed for defects and features such as color, texture, and shape are extracted. These features are then used in a multiclass SVM to classify the fruits as healthy or diseased.

The creators [15] has implemented a CNN based approach in addition to a fourfold cross validation strategy. The original image was cropped and the centre part was taken from it. The image is resized and further rotation has been performed for dataset preparation. The authors have experimented on three different datasets using this model and finally achieved an accuracy of 94%.

2. MATERIALS AND METHODS

2.1 Dataset

Plant Village dataset is an open-source dataset which consist of wide classes of healthy and diseased plant leaf images. Data augmentation has been performed to dataset so as to increase the number of images for training the model.

2.2 Experimental Procedure

The inspiration for this idea was the perspective on how the human brain distinguishes the diseases in a plant, which resulted in the idea of “Disease detection and diagnosis of Agricultural plant leaf using Machine Learning”, to classify the plant diseases by CNN model. The reason for CNN would be because of its in-built multi-layers which reduces the image dimensionality without losing its features. The output of first layer is feed into the succeeding layer. The Features extraction is done automatically hence, no other means is required. The objective was to train the CNN model to make accurate prediction.

In the Convolutional Neural Network (CNN), the input size is reduced by performing convolutional and a filter/kernel is applied on the resultant output. The filter is then moved along the image. After moving across the entire image, the filter then continues to start for image in the next layer and follows the same procedure of moving across that image and follows this until all the layers are traversed. This produces a new matrix from the input image. The pooling layer is a way to reduce the size of the input image and extract dominant features. It works by applying a filter that moves across the image, just like in a convolutional layer. At each step, a function (usually the max function) is applied to the values in the filter. This helps to condense the image and highlight important features. The main reason for the pooling layer is to reduce the possibility of overfitting of features by reducing the spatial dimensions and convolutions. The activation function is applied element-wise to the input matrix, resulting in an output matrix of the same size. The ReLU function is a commonly used non-Linear activation function because it allows for faster learning, it is applied element-wise to the input matrix, resulting in an output matrix of the same size.

2.3 ResNet9

Deep neural networks are hard to train, yet the accuracy is said to be increasing more and more by adding layers of neural networks. But it is a misinterpretation. The problem which may rise is that, the accuracy would tend to get diminish and then degrades quickly on increasing the layers, which might cause vanishing gradient and the curse of dimensionality issues. The vanishing gradient problem occurs when the gradients of the parameters become very small during the backpropagation process, resulting in minimal changes to the parameters. This can happen because the gradients are repeatedly multiplied as they are backpropagated through layers, causing them to become smaller and smaller.

This can make it difficult for the model to learn effectively. In order to solve the vanishing gradient problem, the method proposes a ResNet based solution. Before ResNet, multiple techniques were proposed all the methodologies had very serious issues lagging in precision of producing output. The main objective is that ResNet introduced a “Identity Shortcut Connection” also called as skip connection which solves the vanishing gradient issue as shown in *figure1*.

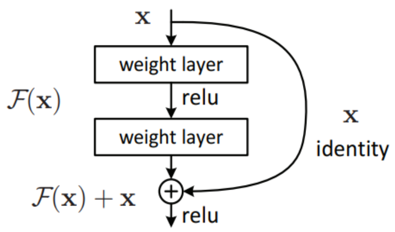

Figure 1: Simple Residual block

The residual block is trying to obtain the output “*y*”. The layers in a residual network are designed to learn the residual, or the difference between the desired output and the input passed through the layers. In other words, the layers are trying to learn "*y*", where "*y*" is the residual. In contrast, the layers in a traditional network are trying to learn the true output *F(x)*. This can be seen in the equation: y = F(x) + x, where y is the residual and x are the input passed through the layers.

$$y = \mathcal{F}(x) + x \qquad (1)$$

Here the use a by-pass connection between the layers for the information to be multiplied with the convoluted output in each layer and is feed into the next layer as input for the next layer which is again split into by-pass connection and convolutional layers. The weight layers are the convolutional layers used for multiplication of image information and the order of the layers get decreased over the model transition.

The idea of skip connections was first proposed in Highway Networks, which has skip connections with controlling gates which decides what information to be passed. Residual blocks are inspired from highway networks with no gate logic in their skip connections. Eventually, the residual blocks allow memory to pass from first to the last layer. Though there are no gates, residual networks out perform any existing highway network.

The model used here RESNET9, comprises of 9 layers of convolutional multiplicative blocks inspired from [14].

We use 3 sets of residual blocks in this methodology as shown in figure2. The first residual block comprises of 2 convolutional blocks internally, made of filters of 1X1 size and having 64 filters, followed by a 1X1 sized filters of 128 numbers, which each block being a batch normalizer block. The output of the first residual block is then split into the identity function and input for the next residual block. The 2nd set of residual blocks consist of a doublet of 1X1 filters of 128 numbers both used successively one after the other. The output of the second residual block is then multiplied with the identity function which is the input to the residual block itself for avoiding the variant grading issue.

The third residual block set consist of two convolution networks each of 1X1 sized filters with first block with 256 number of filters and the second block with 512 number of filters.

The output is combined with the identity function and feed to next and the final residual block. The final residual block consists of a doublet of 1X1 sized filters of 512 numbers each. The output is feed into the max pooling block which is used to flatten the image matrix and is forwarded to a SoftMax block.

SoftMax is a mathematical activation function which is used to converts a vector of numbers into vector of probabilities. The SoftMax function is a widely used activation function in applied machine learning and neural networks of output of a value for each class. SoftMax is approximated as the probability of membership for each class of input which is used. SoftMax is used for mapping the 1D matrix with image features.

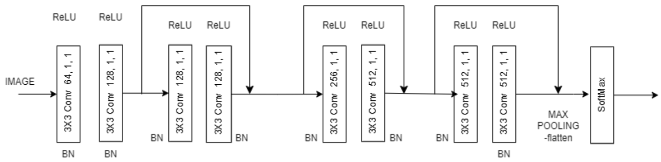

Figure 2: Block diagram of ResNet 9

3. RESULTS

A total of 18850 inputs are used for training purpose and 4730 inputs are used for validation. The dataset was obtained from 'New Plant village dataset'. The entire dataset was divided into ten classes of images with each image per class is shown in table 1. A batch size of 16 was fixed in training phase with a sample batch shown in *figure 3*. Epochs, weight decay, gradient loss and learning rate are the hyper parameters which are used to fine tune the model.

Table 1: Number of images

	no. of images
Tomato___Leaf_Mold	1882
Tomato___Tomato_Yellow_Leaf_Curl_Virus	1961
Tomato___Bacterial_spot	1702
Tomato___healthy	1926
Apple___healthy	2008
Apple___Apple_scab	2016
Apple___Cedar_apple_rust	1760
Strawberry___healthy	1834
Apple___Black_rot	1987
Strawberry___Leaf_scorch	1774

Figure 3: Sample batch

The proposed Resnet model was trained using the training images and classification was performed based on validation dataset. A maximum learning rate of 0.01 was fixed for the model and the learning rate is shown in *figure 4*. Cross entropy loss function is used since it can minimize the loss and increase the accuracy. The loss which occurred during the train and validation phase was represented in the *figure 5*. The different parameters utilized in the model is discussed in the *figure 6*.

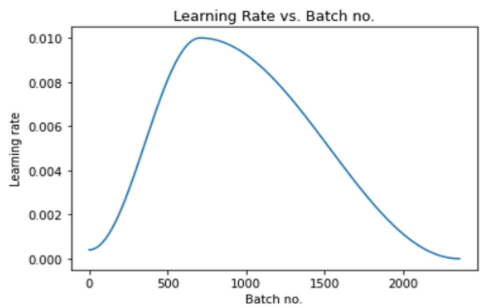

Figure 4: Learning rate

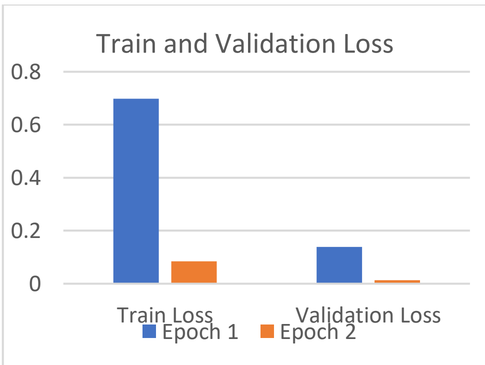

Figure 5: Train and validation loss

```
Total params: 6,575,370
Trainable params: 6,575,370
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.75
Forward/backward pass size (MB): 343.95
Params size (MB): 25.08
Estimated Total Size (MB): 369.78
----------------------------------------------------------------
```

Figure 6: Parameters used in model

Accuracy is calculated using the formula in *equation 2*.

Accuracy is expressed as how much the model can detect from the given input data.

$$accuracy = \frac{No\ of\ correct\ detections}{Total\ no\ of\ detections} \quad (2)$$

A maximum training accuracy of 99.53 was obtained after training the model for two epochs which is shown in *figure 7*. A sample output is shown in the *figure 8*, where the model predicts the correct disease of a plant and suggest the root cause and the appropriate solution to that disease.

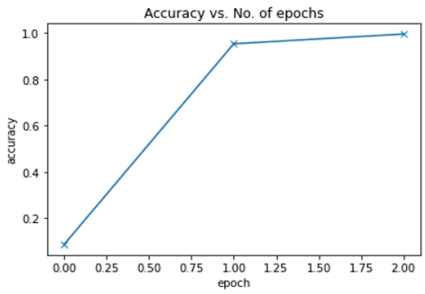

Figure 7: Accuracy graph

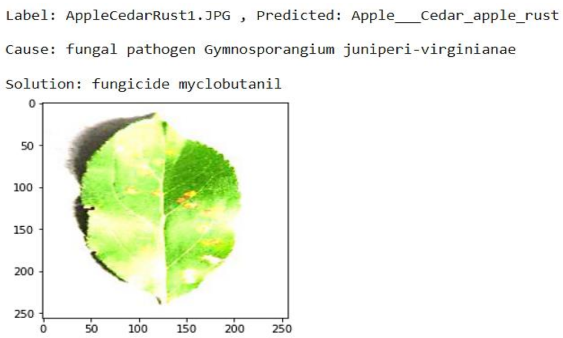

Figure 8: Sample output

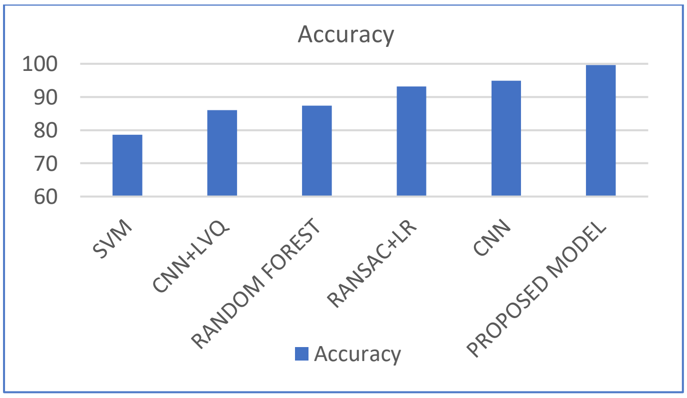

Figure 9: Accuracy comparison for various models

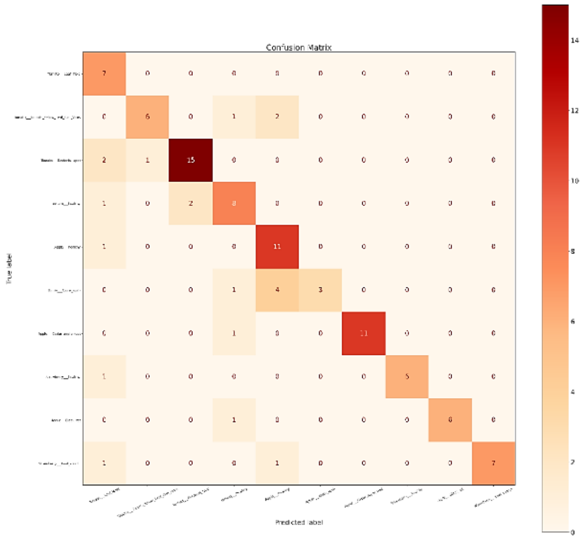

Figure 10: Confusion matrix for the proposed model

4. CONCLUSIONS

The accuracies of various model are compared and proposed model has a better accuracy than the other models as depicted in figure 9. The confusion matrix for the proposed model is depicted in figure 10.

Thus, a ResNet based approach was studied and implemented to detect the disease in various plants. The model was trained using 'New plant village dataset' where the data was split into train and validation dataset. An accuracy of 99.53 was obtained from the model. Apart from identifying the disease its main cause and appropriate solution to the problem is also suggested. Superior accuracy was achieved over the various existing models. In future more classes of images can be included and increase the accuracy.

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