Plant Leaf Disease Prediction Using Deep Learning

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Abstract* — Deep neural networks have proven to be quite effective in picture categorization problems. Here, we demonstrate how neural networks can be used to identify plant infection via picture categorization. We used the Plant leaf dataset, which contains four different types of classes. As a result, the problem we've been dealing with is a multi-class classification problem. As the backbone for our study, we considered three distinct architectures: ResNet50, InceptionV3, and ResNet152V2. On the test set, we discovered that ResNet152v2 produces the best results. We used three measurements to examine the situation: accuracy, review, and the precision disarray metric. We found out that using ResNet152, our model achieves the best results, with an accuracy of 0.984 and precision of 0.91.

***Keywords* — Deep neural networks, multi class classification, NN(neural network)**

I. INTRODUCTION

It is vital to get an exact finding of plant infections for worldwide wellbeing and prosperity. In this consistently evolving environment, recognizing the sickness including early counteraction is essential to stay away from issues that we may confront in. A portion of these issues could devastatingly affect mankind including worldwide deficiency of food.

It is essential to forestall unnecessary misuse of monetary assets accomplishing a better way of life, by tending to climate change with a natural viewpoint. It is hard for the unaided eye of a person to detect all issues with plant sicknesses. Additionally doing this on numerous occasions is likewise difficult and ineffective work. A plant

pathologist must have excellent perceptual skills in order to distinguish distinctive signs and make precise plant disease identification. A robotized framework that can help identify plant illnesses based on the plant's look and visual manifestations could be extremely useful. This can be transported in agricultural areas, with the purpose of automating the entire pipeline. This would not only improve proficiency because machines might do better than people in these repetitive tasks, but it would also increase the efficiency of the activity. Using the concept of computer vision methodologies and deep learning, we address the previously described challenge of computersing plant sickness order.

Plant Disease Detection

Disease identification in plants assumes a significant part in agriculture as farmers have regularly to conclude whether their yield they are reaping is of sufficient quality. It is critical to take these seriously since they can cause substantial problems in plants, affecting the quality, quantity, or usefulness of individual items. Plant diseases generate sporadic outbreaks of illness, resulting in widespread devastation that has a significant economic impact. These issues must be addressed at the root level in order to save people's lives and money. Programmed identification of plant infections is an important research topic because it is very important to inspect large fields of crops and in the early stages, we can recognize the symptoms of illnesses when they appear on plant leaves. This empowers computer vision algorithms

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to give picture based programmed examination. in comparison, manual detection is work escalated, less precise and should be possible just in little regions all at once. With the help of this strategy, the plant illnesses can be recognized at the underlying stage itself and the irritation and disease control apparatuses can be utilized to tackle bug issues while limiting dangers to individuals and the environment.

II. LITERATURE REVIEW

A ton of examination has been done somewhat recently on plant illness identification utilizing profound learning and PC vision. Traditional PC vision calculations such as haar, hoard, filter, surf, picture division, Support Vector Machines (SVM), K-Nearest Neighbors (KNN), K-implies, and Artificial Neural Networks are among the AI techniques (ANN). Plant disease characterization models based on deep learning include the use of a variety of CNN models, such as AlexNet, GoogleNet, VGGNet, and others. Since a rule, when the dataset size is insufficient, multiclass order with a large number of classes necessitates careful hyperparameter adjustment to avoid overfitting, as the model could easily stall out in the near future. [1] makes use of enhanced camera images of infected rice plants. To identify tainted portions of the plants, picture division procedures were used, including K means calculations[2], begins by recognizing the for the most part green hued pixels. The pixels are then covered based on specified limit esteems calculated using Otsu's approach .Then those green pixels that are greater than a certain edge esteem are covered. Additionally, pixels with zero red, green, or blue quality, as well as pixels on the contaminated group's edges, were completely removed [3] utilizations a pre-prepared convolutional neural organization utilizing 1.8 million pictures and uses an adjusting system to move took in acknowledgment capacities from general spaces to the particular test of plant distinguishing proof errand.

III. METHODOLOGY/EXPERIMENTAL

For classification purpose transfer learning is used. The benefit of using transfer learning is as opposed to beginning the taking in process without any preparation, the model beginnings from patterns that have been realized when tackling an alternate issue comparable to the one being mentioned. In this way the model uses past learnings and abstains present earlier without any preparation. "In image classification, transfer learning is normally communicated using pre-trained models. A pre-trained model is one that was built on a large benchmark dataset to deal with a similar problem to the one we're dealing with. We utilized three pre-trained models- Inception v3, ResNet152V2 and ResNet50 as the pre-trained loads for our work.

3.1 Dataset

1951 pictures of infected and solid leaves collected under certain conditions are given as a dataset. Crop infection pair is the pant of every class, and an endeavor is made to foresee the harvest sickness pair provided the picture of plant leaf.

Figure 1: plant disease classes in the dataset

3.2 Image augmentation techniques

All pictures are changed to 224×224 size, advancement of model along with forecasts are being performed on these resized pictures. Make the dataset size practically twofold first dataset size using Data augmentation like shearing, zooming, flipping and brightness. AI algorithms or deep learning algorithms are used along with data augmentation to work on precision grouping. In our project, Keras deep learning library in Python and the picture augmentation strategy was utilized. Activities like Width and stature change, cutting, zooming, level turning, brightness, and filling activities are being performed for ordinary pictures. Picture turn degree was randomly produced from 0 to 45. "Image augmentation" methods used distinctly on typical pictures to adjust the dispersion of the samples over the classes. The quantity of ordinary examples dataset was expanded from 1,583 to 4,266 by playing out the image augmentation procedures. therefore, the quantity of tests for each class was evened out. This equivalent appropriation makes it conceivable to utilize every one of the information as opposed to choosing irregular information during the training process. It is normal that the present circumstance expands the exactness of the preparation and emphatically influences.

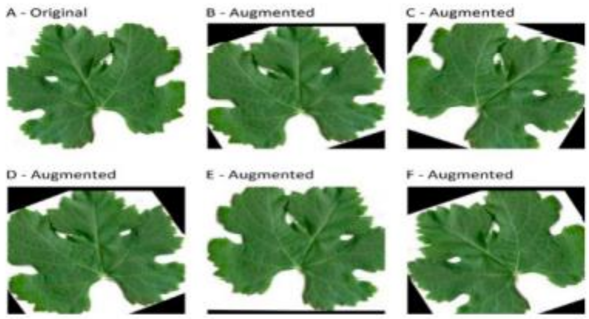


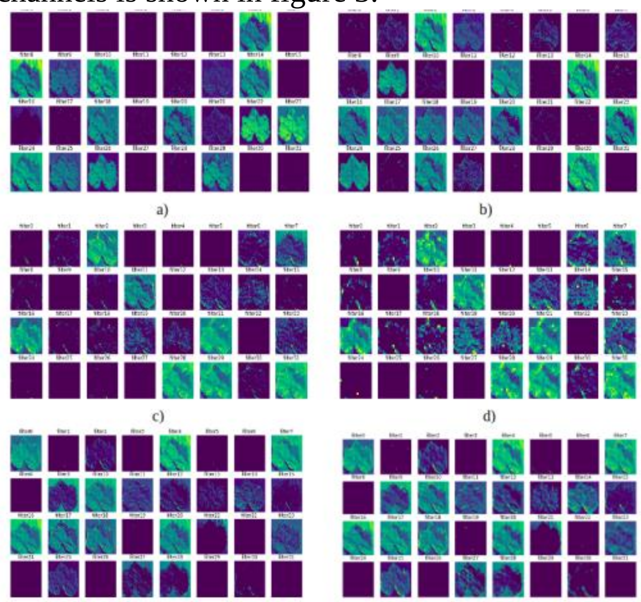
Figure 2: Data augmentation

3.3 Optimization

Constantly changing the weights to achieve best learning was basic objective of the optimization approaches. A procedure of updating is performed by every approach. In the ADAM approach, the weights are adjusted for each occurrence with in the training set for each iteration. As a result, it strives to accomplish the target quickly.

3.5 Visualization of Feature Maps

Feature helps clearing the each layer that the model realizes. The model learns more spatial data as the depth expands. The NN learns edges and blobs in the main layer and finishes the objects in the end. Representation, maps of element is important to get realization of filters at every layer.In the fact of straight forwardness in light of the fact that when a mistake is made by the neural network, hyperparameter tuning can get the justification for turning out badly. The behaviour and functionality of NN can be disclosed particularly stakeholders who wouldn't acknowledge algorithms. And makes expanding and working on general plan as current plan is already known and on how smoothly it works. Can get some view on how good the network has learned by envisioning the learned data. For example a lot of zeros are seen, it will be realized that there are many dead channels which doesn't do much for network, a great chance for pruning to compress model. Four convolution ans four max pooling layers that contain initiation maps for channels is shown in figure 3.



Visualization Layers:

1. 1st convolutional
2. 1st pooling
3. 2nd convolutional
4. 2nd pooling
5. 3rd convolutional
6.3rd pooling

Black boxes are the Neural networks. When the model us sent to underway, element maps prove to be useful as the non technical individuals like partners, specialists, money managers and so forth frequently fail to see the work of neural network.Which makes it simpler to persuade them and acknowledge the outcomes. Model checkpoint and Early Stopping were used while training. Model checkpoint is used when a great deal of time is required to finish and it is smarter to use it and save duplicate just when epoch that further develops the metrics closes. It can be seen that speculation hole for example contrast among training and validation error increases. This indicates overfitting. Mostly a functional and proficient arrangement is about quitting the preparation when the speculation hile is decreasing.

3.6 Model Architecture

The data is divided into three parts- train, val and test sets. Models like Inception V3, ResNet152V2 and ResNet 50 which are pretrained were used by adjusting the ending layers of the NN. Two thick layers and 64 neutrons and 2 neurons were used. The ending layer is used for order with the softmax function for activation. Binary cross entropy is used as loss function. Model was prepared for 25 epochs and the cluster size by changing the hyper boundaries. It assisted the model with trying not to stall out in neighborhood ideal or a saddle point. Assessment metric was multi class log loss. Made two or three information generators: training and testing data. Data generator stacks necessary measure of information (smaller than expected cluster of pictures) straightforwardly from source envelope, changing them to training data and training targets.

IV. Results and Discussions

Evaluation Metric	Inception V3	ResNet152	ResNet50
Accuracy	0.968	0.984	0.942
Precision	0.92	0.91	0.91
Recall	0.94	0.93	0.94
F1	0.93	0.92	0.93

V. Conclusion

Sicknesses in plants are a significant danger to food supply around the world. This paper exhibits the specialized possibility of deep learning utilizing convolutional neural network way to deal with automatic illness detection through picture identification. A public dataset of 1951 pictures that are infected and sound leaves was utilized, characterizing crop species and sickness status of 4 unique classes containing a crop types accomplishing a accuracy of 97.8 percent with residual network architecture by preparing a deep convolutional neural organization. In this paper, another methodology of utilizing deep learning strategies was explored to consequently order and distinguish plant infections from leaf pictures. The created model had the option to recognize healthy leaves and various illnesses, which can be outwardly analyzed. The total strategy was portrayed, from gathering the pictures utilized for training and validation to picture expansion lastly the system of preparing the deep CNN and adjusting. We summed up the eventual outcomes and reached the resolution that ResNet152v2 accomplishes the most elevated precision and accuracy.

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