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RESNEXT-BASED IMAGE CLASSIFICATION MODEL FOR PLANT DISEASE IDENTIFICATION

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Abstract

Advancement in Automation has brought a revolution in the field of agriculture for various applications. Digital image processing combined with Machine Learning techniques can provide support in the area of agriculture by assisting in the classification and detection of plant diseases. In this paper, the ResNext-50 model is presented for the classification of plant diseases and has proved to be more efficient not only in terms of Image Classification but also in terms of Image Segmentation. The model is developed by making a few modifications to the ResNet-50 model and adding some layers. A dataset from Kaggle is used having 87867 images for training and validation. ResNet-50 and ResNext-50 are trained on 25 epochs with 80% images and then validation is done with the remaining 20% images. The ResNext-50 model is found to have better training and validation accuracy than the ResNet-50 model. ResNext-50 model is found to have a training accuracy of 99.65% and a validation accuracy of 94.05% after the last epoch, on the other hand, the ResNet-50 model is found to have a training accuracy of 99.32% and a validation accuracy of 93.45% after the last epoch. The accuracy and loss results have proved the efficiency of the ResNext-50 model over the ResNet-50 model.

Keywords: CNN, Deep Learning, Machine Learning, Plant Disease Classification, ResNext Model.

1. INTRODUCTION

Agriculture is the mainstay of the Indian economy. Various types of plants and crops are being grown asper requirement of society and needs of day to day basic requirements. But the quality and quantity of agriculture is affected by the diseases in plants. The early identification of plants infections is the primary and most crucial activity in agriculture to improvise the quality of plant production for economic growth. Even today, most of the verification is done manually that may not be easy to accurately detect the disease and its type. Advancement in Automation has revolutionized every field and it is also being applied in the field of agriculture for various applications. With the help of artificial intelligence, an automated system can be made able to identify plant diseases with much better accuracy. If the information gathered is proper and accurate, the issue of identificationof plant diseases can be solved effectively. Similarly, there are a number of different diseases affecting plants which results in loss of production to a great extent. Thus, it is of utmost importance to detect, analyze and classify diseases. Digital image processing combined with Machine Learning techniques can help in classification and detection of plant diseases [1]–[4] [1] – [3]. Machine Learning is an art of developing algorithms of models that makes a system capable of learning automatically through experience using some training data without being explicitly programmed. These machine learning algorithms are being applied in various different fields such as agriculture, banking [5], customer services, defense services,

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healthcare and many more. In agriculture, the algorithm can used to train a machine to identify various agricultural problems at an earlier stage [6]. The continuous monitor of the plants by agriculturists is not always possible or financially efficient especially for crops or trees in isolated rural areas. Remote monitoring through sensors, drones, etc, can offer a low cost and high precision alternative option.

Just like machine learning is a subgroup of artificial intelligence, Deep learning is a subgroup of machine learning. As the name specifies, deep learning refers to a system that can learn to think deeper. The structure of Deep Learning models comprises of a multilayer artificial neural network, similar to that of brain. The network is designed so that they can extract information such as, image, voice, text, etc. from the input data, in the course of training using training data. After learning, the neural network can predict the output for new unknown data. Recently, there has been an explosion in the field of Deep Learning due to its capabilities to perform Image Classification, Speech Recognition, Pattern Recognition, Language Translation, etc. Accordingly, Deep Learning architectures have appeared as a superior choice in the field of agriculture, banking, customer services, defense services, healthcare and many more [7]. Commonly used Deep Learning Techniques for Plant disease Classification are K-Mean method, Thresholding, Segmentation, Otsu method, Support Vector Machine[8], [9], Artificial neural network [10] etc. But, Convolutional Neural Networks (CNN) is one of the most accepted and explored techniques of Deep Learning which has proved to be the best for applications that involves image classification. So, the work in this paper discusses about the previous work in the field of plant disease classification and detection in Section 2. Further Section 3 presents the proposed framework and subsequent sections gives explanation of ResNext model used in the work, experimental results and finally Section 6 concludes the paper.

2. LITERATURE REVIEW

With the advancement in Deep Learning techniques, it has been successfully applied in various domains. It has proven its potential in the domain of agriculture by facilitating Plant Disease Identification. A lot of research has been carried out for classification of plant disease using image processing and image segmentation techniques. Different architectures like Support Vector Machines (SVM's), K-Nearest Neighbours (KNN), AlexNet, GoogleNet, and VGGNet, etc have been applied for plant disease classification and disease identification. The introduction of Convolutional Neural Network (CNN) has proved to be a breakthrough moment as it sets the foundation of modern computer vision using deep learning. CNN has emerged as an effective way for analyzing the diseases of plant. There are few segmentation algorithms that can effectively identify common diseases of wheat leaves. An automatic and efficient solution with the use of k-mean clustering is presented for the three common diseases they are powdery mildew, leaf rust and stripe rust [11]. The efficiency of this segmentation method achieved a resultfor 90%. The segmentation task of wheat leaf scab images is based on lab colour space [2]. Genetic Algorithm also used for extracting the features like Shape, size and texture of every wheat leaf image. These images of diseased wheat leaf would be captured with different shape and size. All the wheat

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leaf samples were taken as the RGB images. Though, the recognition rate in this classification process can be improved.

A novel method for robust and early Cercospora leaf spot detection in sugar beet by using hybrid algorithms of template matching and support vector machine (SVM) is proposed [12]. They adopt three stage frame work for achieving the accurate results. It is feasible for continuous quantization under natural daylight conditions which would be implemented to the in-field situation for detection and qualifying the site specific to the plant disease. SVM is very complex in performing calculations. Thus, it is not the cost effective method of testing each instanceand inaccurate to wrong inputs. KNN algorithm is effectual classifier would be used to mi nimize the computational cost. The study done by Rajneet and Manjeet reviews and summarizes some image processing techniques for plant disease detection. A classification approach using KNN for classification of plant disease has been proposed. The approach relies on the calculation of the minimum distance between the given purpose and different points. It is not applicable for huge multiplicity of application [13].

A novel method to detect and classify the plant disease using neural network based classifier is proposed [14]. A comparison based on histogram method, neural network and support vector machine methods is presented. A number of advancements have been made in image segmentation and recognition system. An improved histogram method for image segmentation is proposed [15], which can calculate threshold automatically and accurately. The regional growth method and true color image processing were combined to improve the accuracy and intelligence. But, the number of errors gradually increased with the increase in the number of diseases. An automated way of crop disease identification on various leaf sample images corresponding to different crop species employing Local Binary Patterns (LBPs) for feature extraction and One Class Classification for classification is demonstrated [16]. The methodology used a dedicated One Class Classifier for each plant health condition including, healthy, downy mildew, powdery mildew and black rot. The algorithms trained on vine leaves have been tested in a variety of crops achieving a very high generalization behavior when tested in other crops. Though, the algorithm is not suitable for all environment conditions.

3. PROPOSED ARCHITECTURE

The process of disease classification and detection consists of four basic steps, namely data collection, data conversion, image visualization and image classification.

3.1 Data Collection

The process of automatic disease detection in plants is possible with the help of images or data. Thus it is required to collect appropriate data which can be used to at every step in the process. So, various datasets have been reviewed and the Dataset used in this project is a replica of Plant Village leaf Disease. This dataset is hosted on kaggle under the name New Plant Disease Dataset. This dataset consists of 87867 healthy and unhealthy augmented leaf images divided into 38 categories by species and disease.

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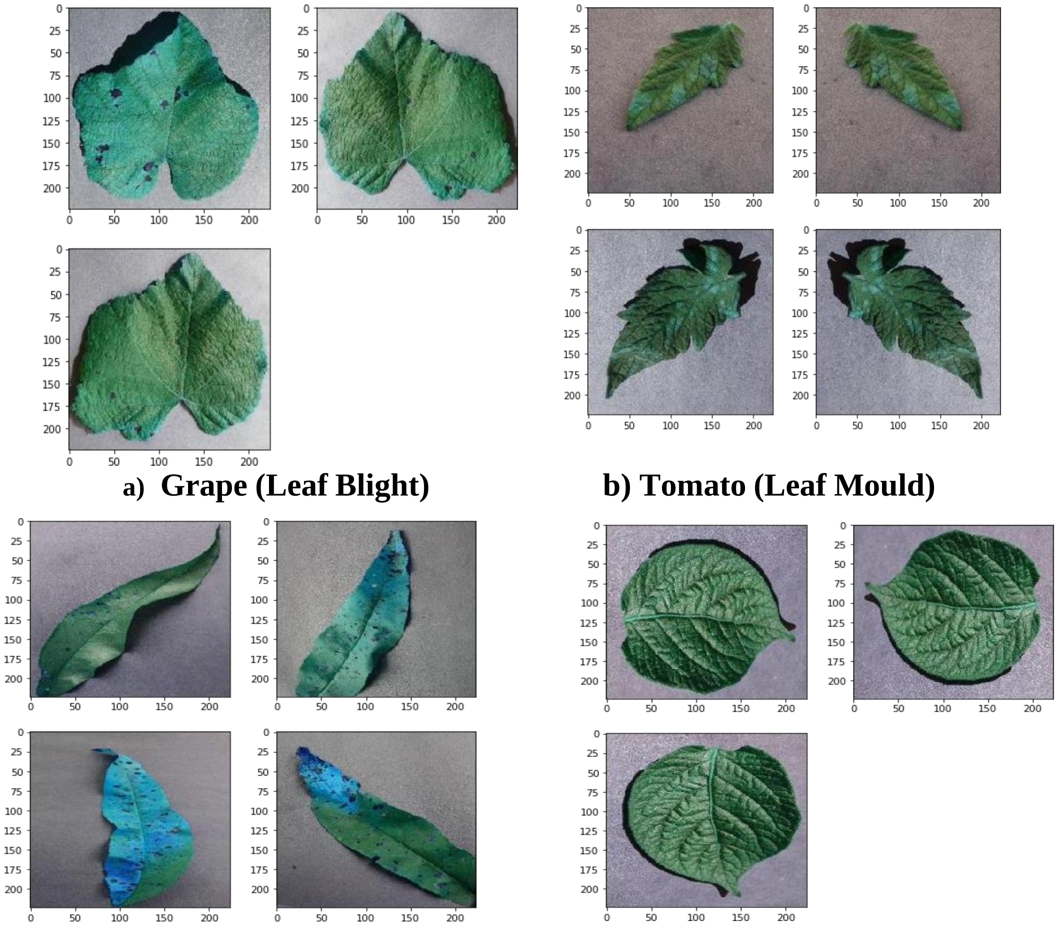
Few categories are Apple_Scab, Apple_Healthy, Peach_Healthy, Peach_Bacterial_Spot. Fig 1 presents some images of healthy and unhealthy from the used dataset with disease specified in bracket. The total dataset is divided into an 80/20 ratio of training and validation set. Thus, the total number of training images is 70295 and the total number of validation images is 17572. Also, this dataset provides 33 test images to test the designed model.



a) Grape (Leaf Blight) **b) Tomato (Leaf Mould)**

c) Peach (Bacterial Spot) **d) Potato (Healthy)**

Fig 1: Images of different varieties of plants from the dataset

3.2 Data Conversion

The conversion of data or pre-processing of collected data is done in order to increase the number of images being used in order to increase the accuracy of disease detection process in plants. As the data may be big enough, but still using simple tools like flip/rotation, brightness, zoom, etc to create new images can improve the accuracy of model. Such tools or processing is termed as Data augmentation and Normalization. The dataset used here is already recreated using offline augmentation from the original dataset. Table 1 represents the completed Dataset is composed of Augmented Images hence total number of augmented

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images are 87867 including both training and testing Images.

Table 1: Dataset for Classification of Plant Disease

S, No.	Category	Healthy/Disease	Training set	Validation Set
1	Apple	Scab	2016	504
2		Black Rot	1987	497
3		Cedar Apple Rust	1760	440
4		Healthy	2008	502
5	Blueberry	Healthy	1816	454
6	Cherry	Powdery_mildew	1683	421
7		Healthy	1826	456
8	Corn	Cercospora_leaf_spot Gray_leaf_spot	1642	410
9		Common Rust	1907	477
10		Northern_Leaf_Blight	1908	477
11		Healthy	1859	465
12	Grape	Black Rot	1888	472
13		Esca_(Black_Measles)	1920	480
14		Leaf_blight_(Isariopsis_Leaf_Spot)	1722	430
15		Healthy	1692	423
16	Orange	Haunglongbing_(Citrus_greening)	2010	503
17	Peach	Bacterial Spot	1838	459
18		Healthy	1728	432
19	Bell Pepper	Bacterial Spot	1913	478
20		Healthy	1988	497
21	Potato	Early Blight	1939	485
22		Late Blight	1939	485
23		Healthy	1824	456
24	Raspberry	Healthy	1781	445
25	Soyabean	Healthy	2022	505
26	Squash	Powdery_mildew	1736	434
27	Strawberry	Leaf_scorch	1774	444
28		Healthy	1824	456
29	Tomato	Bacterial Spot	1702	425
30		Early Blight	1920	480
31		Late Blight	1851	463
32		Leaf Mold	1882	470
33		Septoria_leaf_spot	1745	436
34		Spider_mites	1741	435
35		Target Spot	1827	457
36		Yellow_Leaf_Curl_Virus	1961	490
37		Mosaic_virus	1790	448
38		Healthy	1926	481
Total			70295	17572

3.3 Image Visualization

Image Visualization is the preliminary step for the analysis of any image data which involves transformation and presentation of that image to obtain the features stored in its hidden layer. Image visualization is same as feature visualization or feature extraction. The

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images of plant dataset are transformed by visualization/ activation functions to obtain various features. Feature extraction improves the accuracy of classification and detection of plant diseases. But in this work ResNext model is being used for image classification, and the architecture of ResNext includes transformations of images. Like ResNet, ResNext is also a deep learning model and therefore image visualization is not required to be done individually but included along with image classification.

3.4 Image Classification

The method of recognizing the category of a particular image is Image Classification. Various techniques such as KNN (K-Nearest Neighbor), SVM (Support Vector Machine), PNN(Probabilistic Neural Network), Fuzzy Logic, etc. are being explored for classification and detection of plant diseases. But they suffer from certain disadvantages, like KNN learns slowly, whereas SVM involves longer training time. The storage space required by PNN is more, and Fuzzy Logic has poor performance with increased features. Nowadays, CNN (Convolution Neural Network) is getting popular in the field of image classification. It is made up of several layers including convolutional layers, nonlinearities, pooling layers, and drop-out layers and fully connected layers. In this project efficiency of ResNeXt model for classification of Plant Disease is tested.

4. ARCHITECTURE OF RESNEXT-50 MODEL

ResNeXt-50 is an image classification model that adds a layer of cardinality above its predecessor ResNet, hence the name ResNeXt. This model is selected for Identification and Classification of Plant Diseases, as it has proven its potential not only in terms of Image Classification but also in terms of Image Segmentation. ResNeXt has simple, highly modularized network architecture for image classification. ResNeXt network is constructed by repeating a building block that aggregates a set of transformations with the same topology. This strategy exposes a new dimension, which we call "cardinality" (the size of the set of transformations), as an essential factor in addition to the dimensions of depth and width.

Table 2: Convolution Layers in ResNet-50 and ResNext-50 model

Stage	Output	ResNet-50	ResNet-50 (32× 4d)
conv1	112×112	7×7, 64, stride 2	7×7, 64, stride 2
conv2	56×56	3×3 max pool, stride 2	3×3 max pool, stride 2
		$\begin{bmatrix} 1\times 1, 64 \\ 3\times 3, 64 \\ 1\times 1, 256 \end{bmatrix} \times 3$	$\begin{bmatrix} 1\times 1, 128 \\ 3\times 3, 128, C=32 \\ 1\times 1, 256 \end{bmatrix} \times 3$
conv3	28×28	$\begin{bmatrix} 1\times 1, 128 \\ 3\times 3, 128 \\ 1\times 1, 512 \end{bmatrix} \times 4$	$\begin{bmatrix} 1\times 1, 256 \\ 3\times 3, 256, C=32 \\ 1\times 1, 512 \end{bmatrix} \times 4$
conv4	14×14	$\begin{bmatrix} 1\times 1, 256 \\ 3\times 3, 256 \\ 1\times 1, 1024 \end{bmatrix} \times 6$	$\begin{bmatrix} 1\times 1, 512 \\ 3\times 3, 512, C=32 \\ 1\times 1, 1024 \end{bmatrix} \times 6$

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conv5	7×7	$\begin{bmatrix} 1\times1,512 \\ 3\times3,512 \\ 1\times1,2048 \end{bmatrix}\times3$	$\begin{bmatrix} 1\times1,1024 \\ 3\times3,1024, C=32 \\ 1\times1,2048 \end{bmatrix}\times3$
	1×1	global average pool 1000-d fc, softmax	global average pool 1000-d fc, softmax
#params.		25.5×10^6	25.0×10^6
FLOPs		4.1×10^9	4.2×10^9

The ResNeXt architecture is an extension of the deep residual network which replaces the standard residual block with one that leverages a "split-transform-merge" strategy (i.e. branched paths within a cell) used in the Inception models. Simply, rather than performing convolutions over the full input feature map, the block's input is projected into a series of lower (channel) dimensional. For the purpose of Image Classification new layers were added to the base model of ResNeXt. The added layer includes a convolution layer, a Max pooling layer, a flatten layer and two Dense layer. Two Dropout layer were also added to prevent overfitting.

The structure of ResNext was primarily build upon ResNet Model by replacing each ResNet unit with a ResNext unit. Fig 2 depicts the Convolution Layers in ResNet-50 and ResNext-50 model (The dimensions in bracket shows the shape of residual block and the number outside the bracket is the number of stacked blocks in that layer). ResNext was the first Runner Up in ILSVRC-2016. Compared to its predecessors such as ResNet 101 and ResNet 200, ResNext had 20.1% top 1 error compared to 22.0 and 21.7 for ResNet 101 and ResNet 200 respectively. Also, ResNext has proved to be more efficient not only in terms of Image Classification but also in terms of Image Segmentation.

5. EXPERIMENT AND RESULTS

ResNext model expect image of shape 3 X Height X Width, where Height and Width are expected to be at least 224. The images have to be loaded after scaling the in range [0, 1] and normalized using mean = [0.485, 0.456, 0.406], and standard deviation = [0.229, 0.224, 0.225]. As the dataset of 87867 images is chosen for this work, the data is first given as input and then converted to desired form. The Labels are one-hot encoded and images are resized to suit the requirements of training. The 80:20 Rule is used for the training and validation purpose. Now, both the models ResNet-50 and ResNext-50 are then trained on 25 epochs with 70295 images. After the trainingwas complete, validation is done with 17572 images. The accuracy and loss plot obtained for both the models are shown in Figure 2 and 3 respectively. ResNet-50 model is found to have training accuracy of 99.32% and validation accuracy of 93.45% after the last epoch. On the other hand, ResNext-50 model is found to have training accuracy of 99.65% and validation accuracy of 94.05% after the last epoch.

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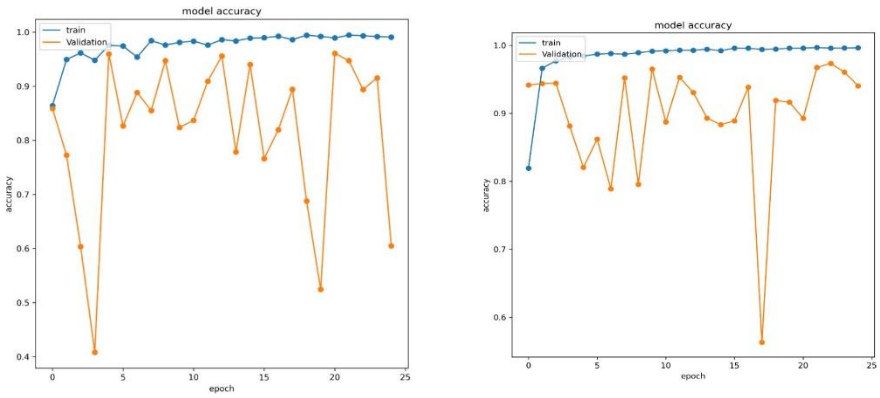

Fig 2: Accuracy of a) ResNet-50 Model for 25 epochs, and b) ResNext-50 Model for 25 epochs

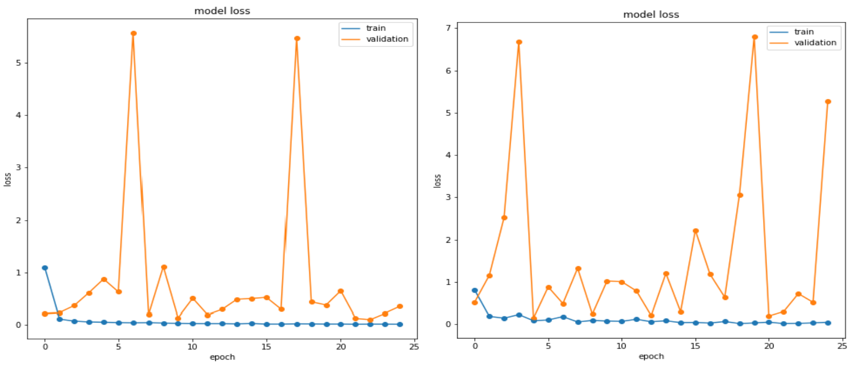

Fig 3a): Loss of ResNet-50 Model for 25 epochs, and b) ResNext-50 Model for 25 epochs

Similarly, the loss after final epoch in case of ResNet-50 is 0.0242 and 5.5421 for training and validation respectively. However, the loss after final epoch in case of ResNext-50 is 0.0107 and 0.3442 for training and validation respectively. Overall, the ResNext-50 model has showed a constructive approach and better results than ResNet-50 model for Plant disease Classification.

6. CONCLUSION

The method of image classification is presented using ResNext-50 model for plant disease detection. A dataset containing healthy and unhealthy augmented leaf images with various diseases of apple, potato, tomato and other fruits is used having 87867 images sufficient enough to test the accuracy of used model. Image classification of plant diseases is achieved by using ResNext-50 model, after doing few modifications and adding some layers in the ResNet-50 model. An average training accuracy of 99.65% and validation accuracy of 94.05% is achieved with ResNext-50 model and also the loss has reduced. The results of training and validation for 25 epochs have showed that the Residual Network model ResNext-50 works superior than ResNet-50 model. Overall, the ResNeXt-50 model showed a constructive approach towards Plant disease Classification. In future work, the same model can be trained with other different varieties of plants and diseases. New augmentation techniques are really helpful in

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increasing and maintaining the quality of datasets. So, with the help of different augmentation techniques, best results can be achieved.

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