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Texture and Colour based Plant Leaf Disease detection using DenseNet

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Abstract:
In the agricultural sector, production in terms of quality and quantity relies on the healthy condition of plant leaf which means the production is affected by the diseases of a plant leaf. A fast reliable non-destructive method uses to detect the issues in the process of diagnosis of plant leaf diseases in early stages which is beneficial for farmers to achieve a higher quality of production. In this paper, Plant Village dataset utilizes to get the images of leaf leaves to include diseases and a healthy class and it is also used as an input source to derive the architectures of deep learning neural networks such as AlexNet, ResNet, and DenseNet. The analysis of accuracy and execution time in classification has been considered based on the number of images and hyper-parameters like weight, mini-batch size, and bias learning rate.

Keywords: *Deep Learning, Image Processing, Plant Disease, AlexNet, ResNet, and DenseNet.*

I. Introduction

In many countries, the national income has been improved by the agricultural industry which is considered as one of the most important sectors. In order to ensure the reliable production and attain the highest quality standards in the production, automated processes and components have been developed in the agriculture industry throughout the years. It is important to note that the cultivation of agricultural products based on an efficient process is developed due to the higher demand in agriculture sector. The production of the agriculture industry is greatly impacted by the diseases and defects of plants and crops that automatically results in the significant economic loss of any country. In the United States, the economic loss of 33 billion dollars is estimated every year which was happened owing to the presence of plant pathogens in crops. The diseases namely huanglongbing citrus and chestnut blight fungus are introduced in the plants with the effect of pathogenic species. However, the diseases can be found in the plants by contributing the insect infestation in addition to the fungal, bacterial, and viral infections. The level of effect of diseases in plants may increase owing to the few factors like changes in temperature and climate.

The infection symptoms spread out on different segments of the plant if in case a plant is infected by the pathogenic species and it lowers the growth of vegetable or fruit consequently. In general, Apple production is considered as a large sector and over 17 million tons of production achieves especially in China country every year. The infections in Apple plants may lead to the decrement in production which is in terms of grade and yield along with the impact of return bloom of the subsequent season. Moreover, the countries completely dependent and chosen the main source of income as an agriculture sector are affected by these features. The farmers have been focused to use the pesticides and chemical products to eradicate the diseases and restrict the losses in the production of the agricultural industry. Although, this solution may help in the reduction of diseases in plants but it has some disadvantages.

The agriculture produce may get into the dangerous levels with toxic features as the pesticides

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are used widely for the growth of plants and a main drawback of using chemical pesticides is that the investment of cultivation becomes higher. The farmers purchase pesticides and commonly used them in fields but they claim that how the usage of chemical pesticides concerns the healthiness and wholesomeness of products. However, it's required to control and usage of pesticides to achieve high-quality products and this method of using pesticide with controlled or monitored manner is called as selective pesticide spraying. Different types of techniques have been improved to reduce production losses due to defective plants. The farmers have used commonly two types of manual techniques such as naked-eye observation and hand inspection. The process of observation from experts is very costly and time-consuming that can be used in the detection and characterization of plants. These techniques are used to sort out the errors and make judgemental errors by various farmers. Most of the problems could be found out in the labor-intensive techniques and the disease detection systems were implemented to overcome these issues.

The health condition of plants has affected by bacterial and fungal viral infections which are introducing the diseases in plants ultimately it reduce the growth of production. To overcome this problem, it's not good to rely always on the usage of chemical pesticides because it is not only being costly but also showing a negative impact on nature as well. To give assistance to farmers to achieve the highest production through the protection of defective plants, it's required to consider some precaution standards in identification and reduction of diseases in plants during the premature phases. The discussion and comparison of current plant diseases detection techniques like hyperspectral imaging and visible imaging will consider in this thesis. To recognize the disease severity in plants, an easy to use system is developed. Accordingly, farmers and agriculturists can make use of the designed system to measure the plant leaf disease severity levels. Additionally, a robotized system is considered and implemented with the automated approach which can be used to monitor the health condition of plant leaf in early times and real-time field environments.

II. Literature Survey

Please Anand H. Kulkarni et al. [1] has improved a methodology by using diverse image processing techniques to identify the diseases in premature stages in plants without compromising on accuracy. In this methodology, ANN-based classifier and Gabor filter have been utilized to get the recognition rate up to 91% and for feature extraction respectively. The calculation of parameters of co-occurrence matrix based on supervised learning has been done with the proposed fast algorithm by F. Argenti et al. [2] and a method of maximum likelihood has been utilized for faster classification. P. Revathi et al. [3] has been developed the homogenize techniques to detect the edges that are named as Sobel and canny filters. The disease spots in classification are identified by using these extracted edge features. The categories of diseases have been derived with the utilization of introduced homogeneous pixel counting techniques for the cotton disease detection (HPCCDD) algorithm and the accuracy level of 98.1% can be achieved based on an existing algorithm. A technique of novel and improved k-means clustering has been developed by Tushar H Jaware et al. [4] for solving the low-level image segmentation. To extract the statistical texture features, a spatial gray-level dependence matrices (SGDM) method was proposed by Sanjay B. Dhaygude et al. [5]. The representation of Hue Saturation Value (HSV) has been converted from RGB images that are included the displaying of H, S, and V components. By using fuzzy c-means classification and auto-cropping segmentation, an empirical investigation is presented by Mokhled S. Al-Tarawneh [6] for the recognition of spot disease in olive leaf. For image enhancement, median filter and RGB to lab color space have been utilized. Finally, k-mean clustering and fuzzy c-means techniques are analysed comparatively.

Yan-Cheng Zhang, et al. [7] has designed an approach of fuzzy feature selection based on fuzzy

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curves (FC) and fuzzy surfaces (FS) in order to choose the disease features in cotton leaf that will lead to achieve the decreased dimensional feature space. Haiguang Wang et al. [8] has been implemented the Back-propagation Networks which are used to make the classification of grape and wheat diseases and also the dimensions of feature data have been decreased with the principal component analysis (PCA). The proposal of texture features has been done by Simona E. Grigorescu et al. [9] that is improved with the Gabor filters' local power spectrum and also discussed the features such as Gabour energy, complex moments, and grating cell operator. The conclusion of this proposal is that texture features are only the factors used for getting a response from grating cell operators. S. Arivazhagan et al. [10] has been developed the texture features which can be used to detect the unhealthy region and classification. This algorithm has been used to test almost a total of ten species of plants that include lemon, banana, jackfruit, tomato, sapota, beans, mango, and potato and achieved an accuracy level of 94.74% using Support Vector Machine (SVM) classifier.

According to the statistical classification, a neural network has been developed by Dheeb Al Bashish et. Al [11] and it is used to detect and make a classification of diseases. However, it could be implemented successfully and achieved a precision rate of around 93%. Song Kai et al. [12] has been identified the research on maize disease image recognition of corn with the implementation of BP networks effectively. In this research, three technologies are used namely BP neural network, Co-occurrence Matrix (CCM) spatial gray level layer, and YCbCr color space technology for classification of maize diseases, for deriving the feature of disease spot texture, and for segmentation of disease spot respectively. H. Al-Hiary, et al. [13] formulated the BP neural networks and discussed the K-means clustering applications for extracting the information of classification and clustering of diseases that impact on the plant leaves. These neural networks are sufficient to detect plant diseases accurately without any errors. Five diseases have been tested by the proposed technique and they are named as cottony and ashen mold, early and late scorch, and tiny whiteness. In order to get a high level extraction for grape leaf colour efficiently with the complex background, ANN has been used i.e. back propagation neural network (BPNN) by Menukaewjinda et al. [14]. Another type of algorithms like a genetic algorithm (GA) and modified self-organizing feature map (MSOFM) have been explored. These techniques are automatically made an adjustment in parameters for color extraction of grape leaf disease. The efficient classification of leaf diseases has been achieved by a very promising technique of Support Vector Machine (SVM). Haiguang Wang et al. [15] has been derived the features of 25 texture, 21 colors, and 4 shapes where reduction of dimensions in feature data processing has been reached by performing the principal component analysis (PCA). For identification of diseases, there are many types of neural networks used as classifiers that include back-propagation (BP) networks, generalized regression neural networks (GRNN), probabilistic neural networks (PNNs), and radial basis function (RBF) neural networks.

III. EXISTING METHOD

A. AlexNet

The AlexNet is the first CNN architecture to be a leading one has shown recognition performance in the ILSVRC competition. It consists of 650,000 neurons and 60 million parameters. A peculiarity of Krizhevsky's approach et al. is the splitting of the network on two graphics cards to limit the memory of 3GB of graphics cards available at the time of development (GTX 580) bypass.

Half of the neurons are each on the two graphics cards, but only a part of the layers across graphics cards to the neurons of the previous layer.

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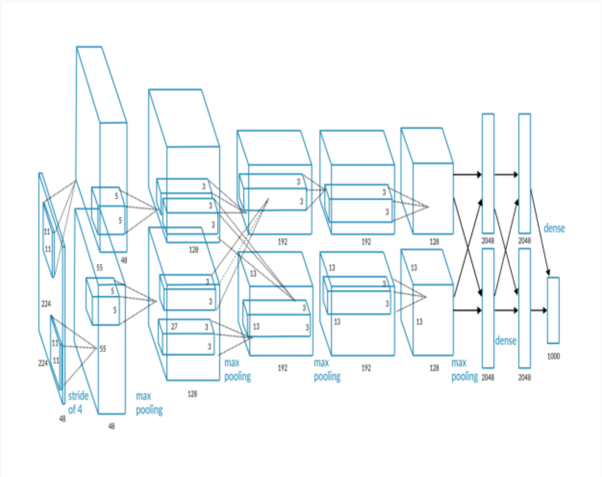

Figure 1: Visualization of the architecture of the AlexNet.

Accesses, as can be seen in Figure 1. This part is as small as possible hold, since the inter-graphics card communication is considerably slower than that Access to graphics card internal memory, but large enough for performance the network does not have a strong negative impact. Based on the 224 × 224 × 3 input image, the detection is carried out with the help of five convolutional layers and three fully connected layers. To Convolutional layers 1, 2 and 5 are max pooling layers by the number of Decrease neurons in the following layers and to be more robust to increase translational changes. The pooling layers have an overlap of the pooling area, which increases the detection performance of the network increased by approximately 0.4% and is expected to further reduce overfitting.

The size of the neural network makes it despite the size of the ImageNet records of 1.2 million images very difficult to avoid overfitting. That's why in addition to the data augmentation of the input data, a dropout within the the first two fully connected layers. Fisher Vectors (FV), which before AlexNet had the best result in ILSVRC Achieved in 2010 complement the Bag of Features approach with a spatial component. Instead of just associating the centroid (class) with a feature save, the distances to the nearest centroids are saved. With the AlexNet outperform the results of the FV procedure by each

rox. 8% with 37.5% top 1 and 17.0% top 5 error s.

Residual Neural Network (ResNet)

esidual neural network (ResNet) [10] is a CNN consists of so-called residual blocks. Such a dual block is shown once in Figure 3.6. A dual block works as follows: Outgoing from an ıt x, either the input image or the output of ther convolutional layer, becomes the first volutional layer, including batch Normalization activation (SReLU), given and then by the second convolutional layer. Before the values are given by the batch normalization and the activation (SReLU) of the second convolutional layer, the input is made x added and then by batch normalization and activation (SReLU) given. The first convolutional layer calculates f (x) as normal second convolutional layer, on the other hand, calculates f (x) + x. The name Residual is moving hence that the rest is also calculated here. The greater depth that is possible with ResNets, the result is that the gradient also through the additional connection is returned and thereby slower becomes smaller. Figure 2 shows the schematic representation of a residual block.

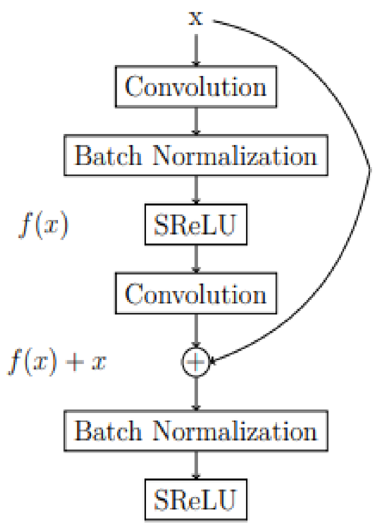

Figure 2: Schematic representation of a residual block.

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It should be noted that if one of the convolutional layers performs a dimension reduction (stride ≥ 2), the addition is no longer possible or.

A dimension reduction must also be carried out here, otherwise the Dimensions no longer match. The paper uses two methods to do this presented. The first method adjusts the dimensions to each other and, if necessary, fills them with zeros. The second carries out a projection, but this requires additional parameters. The experiments in this work use one Modification of the first method by the lambda expression lambda t:

K repeat elements (t [:, :, :: 2, :: 2], 2, 1) is described.

It is because the stride is always 2 × 2, every second value of the output is taken and for the number of filters that are doubled instead of being padded with zeros, the values repeated. The CNNs in experiments 22 and 23 are ResNets. There are three in total Convolutional layer with a stride of 2 × 2 per network. All convolutional layers that come after a convolutional layer with stride double the number of Filters starting with 64 filters (8 × 64, 8 × 128, 8 × 256, 9 × 512). Overall the four residual networks 34 convolutional layers.

The two ResNets of the 23rd experiment (once with 1286 classes and once with 6465 classes) have an additional link over all of them Convolutional layer with the same number of filters. That means, for example, that the output of the eighth convolutional layer, which is the last with 64 filters, the output of the first convolutional layer is added.

IV. Proposed Method

Densely-Connected CNN

A densely connected CNN consists of densely connected blocks. Such a block consisting of four convolutional layers is shown in Figure 3. In a densely connected block, each convolutional layer has every previous one Convolutional layer as input. The filters are attached to each other, so that if all convolutional layers compute ten filters, for example, the input in the third convolutional layer is 20 filters, in the fourth 30 and so on. In the In contrast to the residual blocks, it is not possible to have a convolutional layer with a stride ≥ 2 within a densely connected block, with the exception of the last convolutional layer.

Through these many additional connections between the convolutional layers it is possible that a convolutional layer requires very few filters. Two variants were tested in the paper, one with 12 filters and one with 24 filters. Convolutional layers of the networks in the 24th experiment have 16 filters and a total of 69 convolutional layers, four blocks with 16 convolutional layers plus three Convolutional layer with stride 2 × 2 and one for input and output.

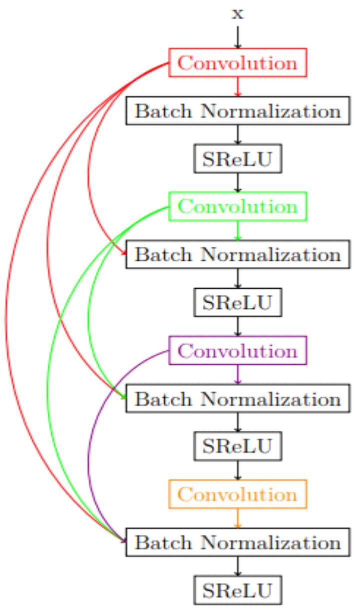

Figure 3: Schematic representation of a densely connected block.

V. Results

This section presents the experimental results conducted in the research. Potato leaf images from Plant village dataset are used for experimentation. The potato plant has two types of leaf diseases, namely, early blight and light blight. The figure.4. Shows the images of sample plant leaves.

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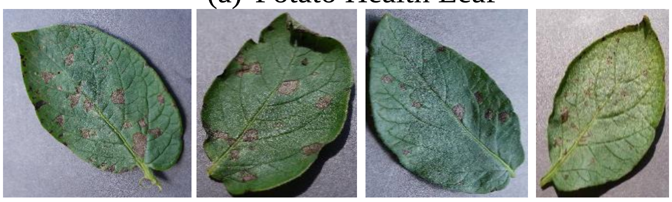
(a) Potato Health Leaf



(b). Potato early blight leaf

(c). Potato late blight leaf

Fig.4. Sample potato leaf images.

In the experiment, AlexNet, Resnet and DenseNet have been used. The confusion matrices and the accuracies obtained by each of the network have been presented in this section. The table 1 shows the confusion matrix for Alexnet. Validation accuracy for potato early blight is 93.64%. Validation accuracy for potato late blight is 94%. Healthy potato validation accuracy is 87%. Overall validation accuracy is 93.32.0%.

TABLE 1
Confusion Matrix for Alex Net

	Potato Healthy	Potato Early blight	Potato Late blight	Total
Potato Healthy	87	5	8	87%
Potato Early blight	10	280	9	93.64%
Potato Late blight	22	26	752	94%
				Total 93.32%

The Table.2.shows the confusion matrix for Alexnet. Test accuracy for three different level of potato leaf, early blight, light blight, and healthy. Test accuracy for potato early blight is 90.38%. Test accuracy for potato late blight is 93%, Potato healthy leaf test accuracy is 86.5% and overall test accuracy is 90%.

TABLE 2
Test output for AlexNet

	Potato Healthy	Potato Early blight	Potato Late blight	Total
Potato Healthy	173	18	9	86.5%
Potato Early blight	3	47	2	90.38%
Potato Late blight	5	9	186	93%
				Total 90%

The Table.3. shows the confusion matrix for ResNet. Validation accuracy for different levels of potato. Validation accuracy for potato early blight is 90.96%. Validation accuracy for potato late blight 95.25%. Validation accuracy for potato healthy leaf is 90%. Overall validation accuracy is 93.74%.

TABLE 3
Validation output for Res Net

	Potato Healthy	Potato Early blight	Potato Late blight	Total
Potato Healthy	90	3	7	90%
Potato Early blight	14	272	13	90.96%
Potato Late blight	17	21	762	95.25%
				Total 93.74%

The Table.4. Shows the Confusion matrix for Res Net. Test accuracy for potato early blight is 91.50%.

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Test accuracy for late blight is 94.5%. Test accuracy for potato healthy leaf is 91.50%. Overall test accuracy is 92.92%.

TABLE 4
Test output class for Res Net.

	Potato Healthy	Potato Early blight	Potato Late blight	Total
Potato Healthy	183	12	5	91.50%
Potato Early blight	2	48	2	92.3%
Potato Late blight	4	7	189	94.5%
				Total 92.92%

The Table.5. Shows the confusion matrix for DenseNet. Validation accuracy for potato early blight is 99.9%. Validation accuracy for potato late blight is 100%. Validation accuracy for healthy potato leaf is 100%. The overall Validation accuracy is 99.9%.

TABLE 5
Validation output for DenseNet

	Potato Healthy	Potato Early blight	Potato Late blight	Total
Potato Healthy	92	2	6	92%
Potato Early blight	5	279	15	93.3%
Potato Late blight	12	19	769	96.12%
				Total 95.07%

The Table.6. Shows the confusion matrix for DenseNet. Test accuracy for potato early blight is 94.2%. Test accuracy for potato late blight is 95.5%. Test accuracy for healthy potato is 92.5%. The overall test accuracy is 93.5%.

TABLE 6
Test output for DenseNet

	Potato Healthy	Potato Early blight	Potato Late blight	Total
Potato Healthy	185	6	9	92.5%
Potato Early blight	1	49	2	94.2%
Potato Late blight	3	8	189	94.5%
				Total 93.5%

VI. CONCLUSION

Based on pre-trained deep learning architecture including AlexNet, ResNet and DenseNet the classification of plant leaf disease has been evaluated by using the Plant Village images' dataset. DenseNet is providing a good performance in the classification accuracy using 13,262 images which are showing better results when compared to the AlexNet and ResNet. By making changes to the number of images, altering the weight and bias learning rate, and putting different kinds of mini-sizes, the output or performance of models has been analyzed in this paper. The performance of models has been affected by the number of images significantly which improves to attain the maximum accuracy. AlexNet didn't provide any relation to the classification accuracy by fine-tuning the mini-batch size and the accuracy is decreased if the mini-batch size is increased in DenseNet. In a similar manner, the accuracy is reduced in Res Net initially and increased rapidly after reaching the learning rate to 30 by fine-tuning the bias learning rate and weight. If the weight and bias learning rate is enhanced, the accuracy in DenseNet is reduced.

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