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Apple Leaf Diseases Identification Using Deep Learning

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Abstract-The healthful growth of the apple business depends on the prompt and accurate identification of apple leaf diseases. Typically, each of these illnesses is examined by knowledgeable professionals individually. This is a laborious task with erratic precision. We thus suggested a low-cost, stable, high accuracy approach for identifying apple leaf diseases in this work. The Mobile-Net concept is used to achieve this. First of all, it is simple to install on mobile devices, it is a low-cost Model when compared to typical deep learning models. Second, with the aid of an algorithm, anybody can successfully complete the apple leaf diseases examination rather than only seasoned professionals. Thirdly, Mobile-Net's accuracy is almost on par with that of current sophisticated deep learning models. Finally, various studies have been conducted to show the efficacy of our suggested strategy for identifying apple leaf diseases. We evaluated the effectiveness and accuracy to well-known CNN models, MobileV3, ResNet152 and InceptionV3. The datasets for apple disease (containing the classifications complicated, frog-eye leaf spot, healthy, powdery mildew, rust, and scab) .

Index Terms- Apple leaf diseases, Mobile device, Mobile-Net, Deep learning.

I.INTRODUCTION

Apple is one of the most prolific fruit varieties in the world, with a high nutritional and therapeutic value. However, a number of illnesses, including Apple Complex, frog eye leaf spot, powdery mildew, rust, and scab, regularly impact the quality of fruits, resulting in significant economic losses in the apple industry. The majority of skilled professionals currently inspect apple leaf diseases, every apple leaf has to be examined. This is a significant task. There are sufficient leaves on one apple tree. We don't have enough qualified professionals to complete this type of examination for a whole apple harvest. Additionally, fatigue will cause these specialists to make a lot of mistakes, particularly when it comes to certain identical leaf ailments. As a result, an algorithm is required to assist farmers in finding a solution. With the use of this algorithm, novice farmers will be able to recognize these apple leaf diseases on their own. These three benefits should be included in this algorithm:

- Stable: The technique should be able to recognize illnesses that affect apple leaves in a comparable way.

- Low Cost: The technique is easily adaptable to mobile devices.

- Efficiency & Accuracy: The illness should be recognized with high accuracy in less than one second.

These three factors, nevertheless, cannot be adequately addressed by present research in order to identify apple leaf diseases. We categorize existing approaches into two groups: examination by skilled professionals and inspection using deep learning techniques. On the other side, a Model for detecting illnesses of apple leaves was created. A CNN mobile model, Its accuracy is very comparable to that of the common CNN model. In the interim, its efficacy is sufficient for identifying diseases in apple leaves. In order to make the disease identification as stable as possible, we gathered a range of leaves with different apple leaf ailments in the initial part of our approach. Six courses were mostly used to demonstrate the effectiveness of our recommended approach. In order to solve the low-cost issue, the model is also utilized to diagnose apple leaf diseases. This is because mobile device deployment is so straightforward. Finally, in order to achieve the goal of high efficiency and accuracy, the Mobile-Net model is modified in line with the characteristics of apple leaf diseases. Additionally, we have tested a variety of models. Therefore, the Mobile-Net idea is the ideal choice. Accuracy and effectiveness are balanced when apple leaf diseases are diagnosed using Mobile-Net.

II. Traditional Apple Leaf Diseases Inspection Method

In the past, trained specialists have employed eye inspection to diagnose plant diseases. However, because perception is subjective, the efficacy and accuracy of recognition might vary greatly. In reality, it is challenging to fully carry out the previous operation. This is because checking the leaves of just one apple tree would require a lot of labor. But only trained experts are capable of completing such a task. Additionally, the inspection process is erratic since the professionals will become weary. Therefore, some stable, low-cost, high-efficiency-precision approaches should take the place of the conventional apple leaf diseases inspection method. Since deep learning has recently made significant progress, it can be employed for this purpose.

III. Dataset Construction For Obtaining Stable Identification Result

Currently, skilled professionals are mostly responsible for inspecting apple leaf diseases. Apple leaves must be examined one by one. This is an impossible feat, though. Because even one apple tree's quantity of leaves is too great for a person to count. Experts can only examine a very tiny portion of the apple trees in this particular apple harvest. According to the tiny number of sample checks, the apple leaf diseases can only be predicted by specialists using their past experiences. A very unstable inspection result will come from this. The detection of apple leaf diseases, however, can only be done by a very small number of professionals. Their load is too much. When they are worn out, incorrect apple leaf illnesses will be assessed. Therefore 18000 thousand images are used for training and testing a model in order to get the better result.

IV. The Mobile-net Model For Apple Leaf Diseases Identification

This section will introduce the Mobile-Net model for identifying illnesses in apple leaves.

The CNN architecture for mobile devices is called Mobile-Net. A depth wise separable convolution is a type of factorized complexity that converts a standard complexity into a depth wise complexity, and a 1 x 1 complexity is known as a point wise complexity. This is how the core architecture is formed, as seen Figure 1 displays batch normal and ReLU after depth wise separable convolutions using depth wise and point wise layers. The model also includes two simple global hyper-parameters that effectively balance latency and accuracy in the interim. The purpose of the width multiplier is to evenly thin a network at each layer. The input image's size is reduced by the resolution multiplier, which also reduces the internal representation of each layer by the same multiplier. The kernel size for a feature map of size DF x DF is Dk x Dk, the input channel is M, and the output channel is N. The following equation may be used to express the overall computation CM amount for the network's core layers:

$$C_M \text{ ¼ } D_k \cdot D_k \cdot \alpha M \cdot \rho D_F \cdot \rho D_F \text{ þ } \alpha M \cdot \alpha N \cdot \rho D_F \cdot \rho D_F; \qquad \text{EQ1}$$

Here, we set the width multiplier to 1 and the resolution multiplier to 1 in our experiment for the identification of illnesses in apple leaves. In the same circumstance, Eq. 2 may be used to determine the computing cost CS of the common convolutions:

$$C_S \text{ ¼ } D_k \cdot D_k \cdot M \cdot N \cdot D_F \cdot D_F; \quad \text{EQ2}$$

Finally, the reduction R in our technique may be determined by Eq. 3 in order to express the conventional convolutions into depthwise convolutions and pointwise convolutions.

$$R \; \frac{D_k \cdot D_k \cdot \alpha M \cdot \rho D_F \cdot \rho D_F \text{ þ } \alpha M \cdot \alpha N \cdot \rho D_F \cdot \rho D_F}{D_k \cdot D_k \cdot M \cdot N \cdot D_F \cdot D_F} \qquad \text{EQ3}$$

The main benefit of this model is that it includes two straightforward global hyper-parameters to efficiently balance the latency and accuracy. The width multiplier and resolution multiplier, two hyper-parameters, enable the model builder to select the appropriate size model for the application based on the constraints of the issue.

V. The High Precision Models For Apple Leaf Diseases Identification

Actually, we have tested a number of deep learning models in order to find the best answer for apple leaf recognition challenges. High efficiency and precision are the primary goals. It goes without saying that these two goals must be balanced. High efficiency may be achieved by running the MobileNet model.

VI. The ResNet152 Model For Apple Leaf Diseases Identification

Two convolutional layers make up the fundamental framework of the ResNet model, which was initially presented in 2015. In the meantime, this model uses a non-parameterized shortcut connection to skip blocks of convolutional layers and adds new inputs into the network and produces fresh results. ResNet18, ResNet34, ResNet50, ResNet101, and ResNet152 were presented as a family of several deep neural networks with identical topologies but varying depths.

Because ResNet152 has the best accuracy among the ResNet models, we chose it as the comparison model in this study.

The ResNet152 model receives an apple leaf with illnesses as input. There are accordingly 10 layers, 24 layers, 108 layers, and 10 layers in each of the four columns. There are 152 layers altogether. The layers inside the dashed box indicate n duplicate convolutional layers, while the dotted shortcuts in this example enhance dimensionality. Dashed box x 5 denotes 5 duplicate convolutional layers, for

instance.

VII.The InceptionV3 Model For Apple Leaf Diseases Inspection

VIII.

A GoogleNet module is called Inception. This model is capable of doing many convolutional or pooling processes in parallel on the input pictures and combining all the results into an extremely detailed feature map. As a result, it should have more precision than generic models.

The Inceptionv3 architecture, the winner of the 2014 ILSVRC, contains 44 layers and 21 million learnable parameters, making it the most effective model of Inception. There are 11 Inception modules in the InceptionV3 model. The first through fourth and tenth through eleventh Inception modules of InceptionV3 employ (a). The fifth through ninth Inception modules of InceptionV3 employ (b). It is a time-consuming model, nevertheless. Convolutional factorization was suggested as a solution to this issue in order to lower its parameters. A 5*5 filter convolution, for instance, may be divided into two 3 3 filter convolutions. The parameters in this method are reduced during this phase from 5 * 5 = 25 to 3*3 + 3*3 = 18. As a result, it reduces the number of parameters by 28%. However, the calculation cost still falls short of fully meeting the efficiency requirements for identifying apple leaf disease.

fig 01: images from training dataset with class label

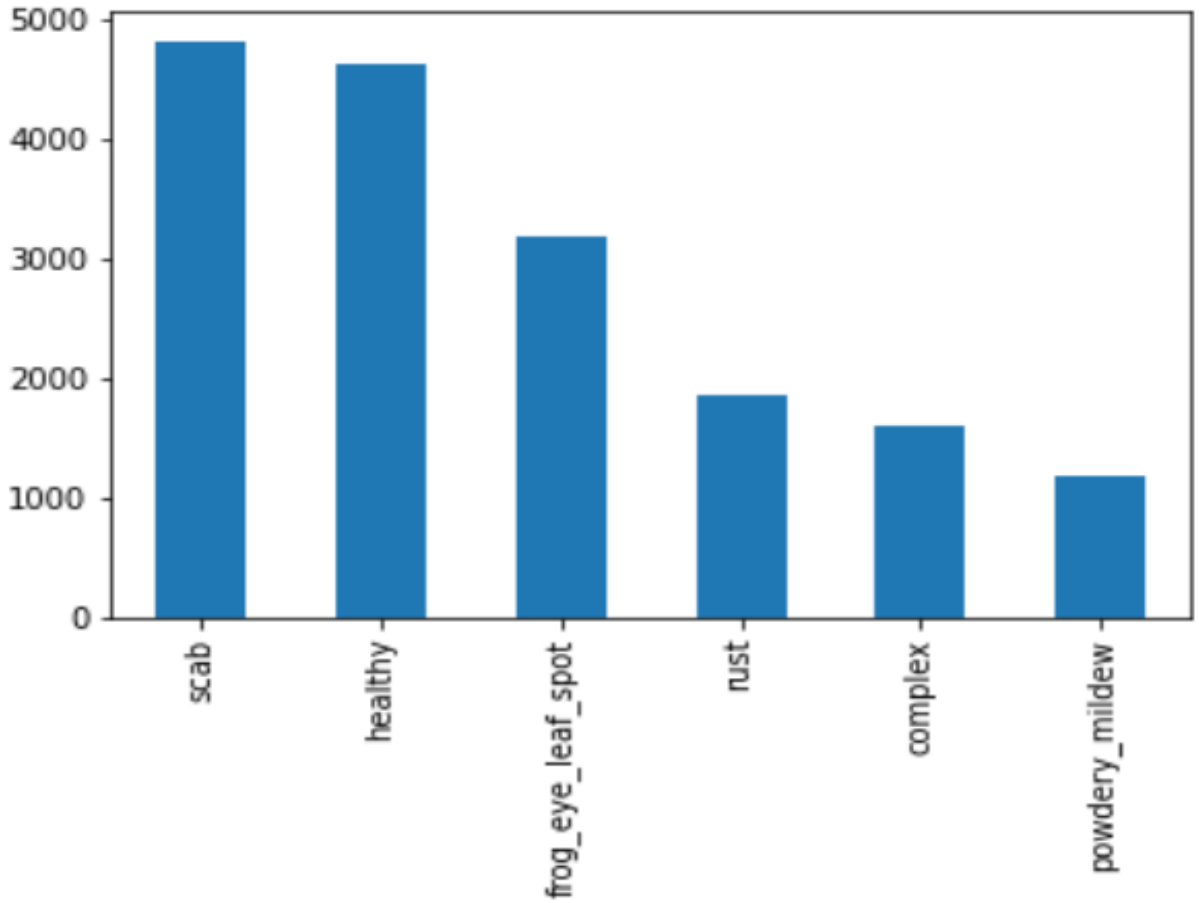
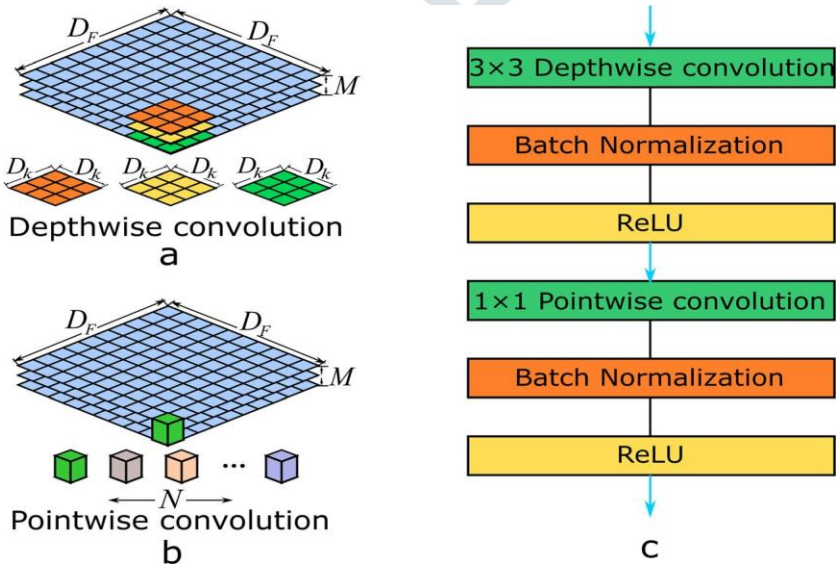


fig 02: trained data info.

IX.Results Of Apple Leaf Diseases Identification Using 3 Kinds Of Deep Learning Models

Deep learning models	Accuracy	Average handling time (s) for each image
MobileNet	91%	0.13
InceptionV3	75.59%	0.45
ResNet152	77.65%	0.79

Fig.3: Neural Network Architecture of MobileNet. a Depthwise Convolution layer. b Pointwise Convolution layer. c Depthwise Separable convolutions with Depthwise andPointwise layers followed by batchnorm and ReLU



We have tested ResNet152 and InceptionV3 for the detection of apple leaf diseases in an effort to get a high inspection precision.

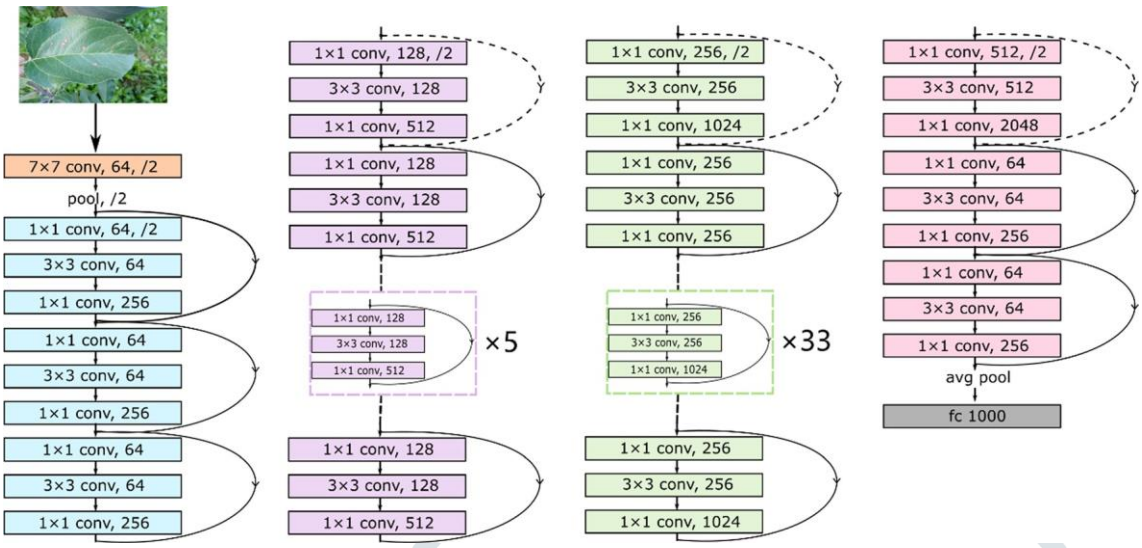


fig.4: neural network architecture of resnet152. the dotted shortcuts increase dimensions and the layers inside the dashed box represents *n* duplicateconvolutional layers.

X. DataSet

The Mobile-Net model was trained and tested using a dataset of 18000 images. The agricultural specialists that visited and surveyed various types of orchards are the ones who gathered all of the pictures. An image generator object was developed to perform random rotation, cutting, and grayscale operations on this dataset in order to increase the accuracy of apple leaf diseases diagnosis. The dataset is enlarged using the aforementioned techniques. In the meanwhile, the recognition accuracy will significantly increase, especially if the photographs are shot in a different rotation or scaling.

Experiment Results And Analysis

We will provide the testing findings in this part using three different deep learning models: Mobile-Net, InceptionV3, and ResNet152. The effectiveness of convolution neural networks and the typical handling time for each picture will be used to demonstrate the findings.

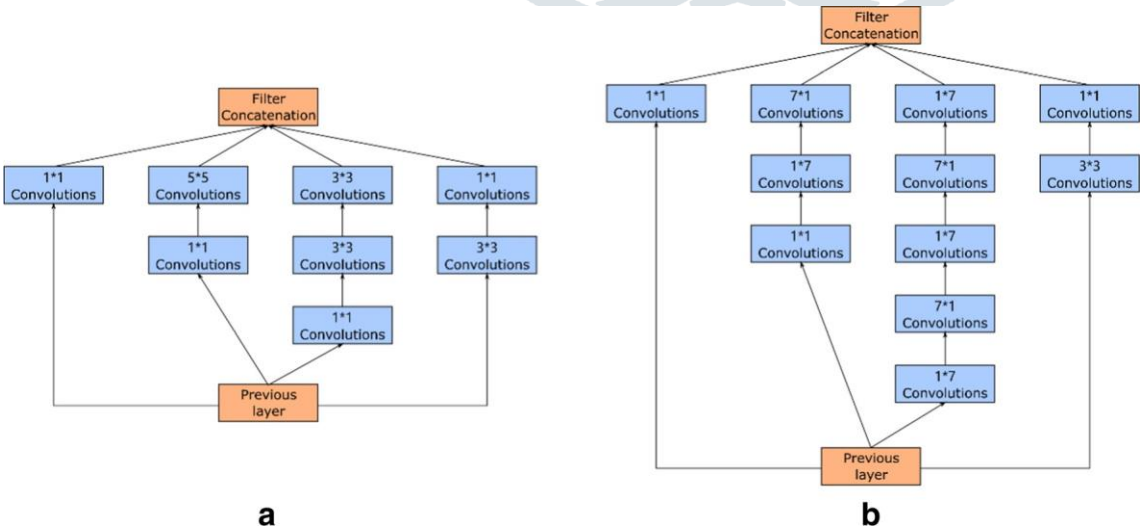


fig.05: neural network architecture of inceptionv3. the model of inceptionv3 consists of 11 inception modules. a is used in the 1th~4th and the10th~11th inception modules of inceptionv3. b is used in the 5th~9th inception modules of inceptionv3.

XI.Conclusions And Future Approach

A strategy for identifying apple leaf diseases using Mobile-Net model is suggested in this study. By using this technique, the need for professionals to identify apple leaf diseases can be significantly reduced. It may provide a reliable identification outcome. Due of its simplicity of deployment in a mobile device, the technology is also inexpensive. Additionally, we offer a decent balance between effectiveness and accuracy, which is accomplished by contrasting several deep learning models. Another future work is to build an android or web app to detect the an apple leaf on real time.

XII.References

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