COTTON LEAF DISEASE DETECTION USING ResNet152V2

I . INTRODUCTION

One of the key factors that impacts the loss of yield in crop production and agriculture is the identification and diagnosis of plant diseases. The designed algorithm and model are intended to be successful in the search for cotton leaf disease in cotton leaves, with the afflicted plant or cotton being identified primarily by its leaves. Finding the cotton leaf disease is significantly simpler by spotting the numerous colored dots and arrangements on the leaf. In order to detect diseases and gauge the general health of the plant, we will use the leaves as our central instrument .

- Colab link https://colab.research.google.com/drive/1Ul82khVk9YM8pu-U1e-aaiCu8LT_d-4h?usp=sharing

II . DESCRIPTION OF THE NETWORK ARCHITECTURE

In their study, Shaoqing Ren, Kaiming He, Jian Sun, and Xiangyu Zhang introduced the Residual Network (ResNet), one of the well-known deep learning models, in their study. Deep Residual Learning for Image Recognition was the title of the study in 2015. One of the most widely used and effective deep learning models to date is the ResNet model.

However, to implement this architecture, we have used the ReLU activation function in the hidden layers and Softmax activation in the output layer. Without implementing this skip link in ResNet, the input "x" is multiplied by the layer weights in this architecture before a bias term is included.

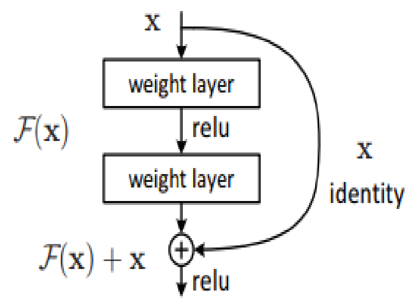

Figure 1 : ResNet Architecture

The activation function f is applied after that, and the result is H(x).

$$H(x) = f(wx + b)$$

The output has altered as a result of the skip connection.

$$H(x) = f(x) + x$$

The 34-layer simple network design used by ResNet, which was influenced by VGG-19, is followed by the addition of the shortcut connection. Following that, the architecture is transformed into the residual network using these shortcut connections.

Instead of learning unreferenced functions, ResNets learn residual functions with reference to the layer inputs. Instead of expecting each few stacked layers to directly match a desired underlying mapping, residual nets allow these layers to suit a residual mapping. They build networks by piling residual blocks on top of one another; for example, a ResNet-50 uses fifty layers of these blocks. We used ResNet152V2 with 152 layers in this case.

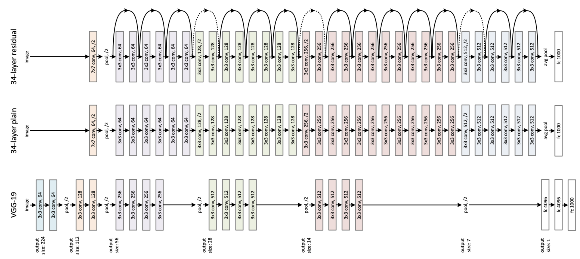

Figure 2 : ResNet 152 Architecture

Ⅲ. ABOUT THE DATASETS

This is a collection of photos that have been used for specific purposes. In total, there are nearly two thousand photos. For preprocessing and classification, we use a cotton leaf dataset divided into three sections: train, test, and val. Over 2,306 photos of various plants and leaves are included in the cotton leaf dataset. This collection includes plants and leaves that are both healthy and sick. We train the dataset to detect the condition of each leaf or plant in this section.

- DataSet Link : Download
- DataSet link in Kaggle : Click

Ⅳ. PERFORMANCE OF THE MODEL

In this project implementation, we have used the RESNET152V2 architecture in order to detect cotton leaf disease. ResNet is one of the most popular CNN architectures introduced in 2015, widely used in image classification and detection.

However, after implementing, we have found that the accuracy rate of the ResNet model in our project is roughly around 98%. Hence, this model could be able to detect almost all the leaves that are infected by the disease.This accuracy figure is from our implemented code.

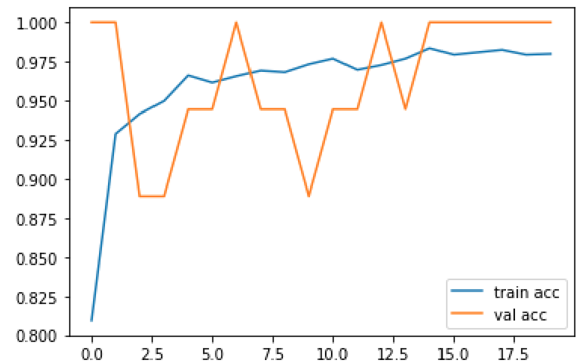

Figure 3 : Accuracy Plot

Ⅴ. SUMMARY

The combined ResNet approach improves the model's feature extraction capabilities while reducing computation time without sacrificing discriminative construction. The proposed model performed well on both the large repository and the cotton disease image dataset, as evidenced by the results analysis.

A forum for farmers to discuss and analyze current trends in various diseases will be added in the future.