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Leaf Fungicide Recommendation using EfficientNetV2B0

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Abstract

Around a quarter of the crop is lost to pests and diseases every year. The biggest problem is the lack of knowledge about the condition and its treatments. In total, billions of dollars every year are being used in fungicides, out of which millions worth of wrong pesticides are incorrectly used. Early detection and diagnosis are the most significant practice for eradicating leaf diseases. For a long time, people have been working in this field, but the results were not appropriate enough. To achieve this, we discuss a solution that identifies the plant disease and provides a solution for cure using a Transfer learning-based Convolution Neural Network (CNN). EfficientNetV2B0 is the pre-trained model used in this paper. In this paper, we classify different diseases of apples, potatoes, and tomatoes. The quantity of crop loss will be reduced if leaf disease is detected early and diagnosed. Due to a lack of knowledge about fungicides, some farmers are either applying the wrong or excessive fungicides, damaging the soil and food. This will help in using a suitable solution in a suitable amount. So we can have healthy crops and reduce soil pollution.

Keywords

Transfer Learning, EfficientNetV2B0.

INTRODUCTION

Food, as well as oxygen, are important for life. Plants play a prominent part in their production. Pests and diseases wreak havoc on 20-40% of agriculture products every year. Each year, approximately 300 billion dollars is spent on the treatment of plant diseases around the world. The human population, on the other hand, is growing at an annual rate of 83 million people. If the population is growing at this rate and crops are lost to diseases and pests, the food chain will become unbalanced, resulting in a food crisis.

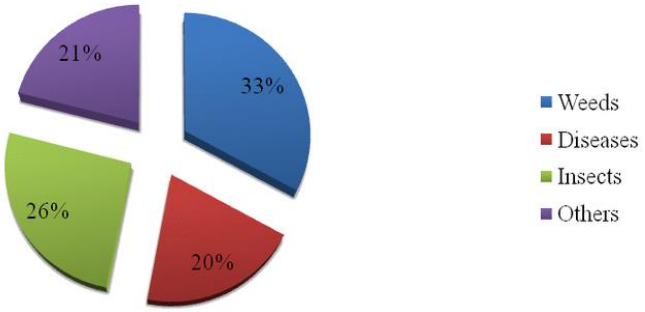

Figure 1 Types of causes for loss in crop

Early detection and treatment with appropriate fungicides are required for these diseases. The disease is hard to trace for farmers. A major issue is a lack of understanding about diseases and treatments. Fertilizers and fungicides are sometimes used in overabundance, which is bad for the soil and the people who consume them. As a result, advanced techniques should be used to detect diseases and cures more quickly and precisely.

It is quite challenging to Manually diagnose leaf disease using leaf photos. In this paper, a transfer learning CNN model is used to describe such an application. It takes an image as input and categorizes it according to its disease, and recommends a solution. This can reduce disease and increase crop yield. This application categorizes diseases that affect apples, potatoes, and tomatoes. When compared to other existing methodologies, our approach gives the most accurate results in the shortest amount of time. It can also take photographs and detect the disease. This may also be enhanced and deployed to keep a watch on a broad area spread crop while sprinkling fungicide with drones. This automation technique can assist farmers in reducing their labor hours and workload.

RELATED WORKS

Many research works on automating the categorization of leaf diseases have been conducted up to this point. Below listed are some of the disease detection techniques developed previously.

I. To categorize plant diseases, N.Kanaka Durga [2] employed the SVM and ANN algorithms. Both the SVM and the ANN are trained on the same dataset. SVM is a supervised machine learning technique.SVM is a supervised machine learning technique. Artificial neural networks, or neural networks, are machine learning algorithms inspired by the nervous system of animals. The outcomes were 70-75 percent for SVM and 80-85 percent for ANN, respectively.SVM and ANN, on the other hand, were outperformed by KNN [3].

II. KNN was used by Sandeep Kumar [3] to detect leaf disease. It is a supervised machine-learning algorithm. The 'K' symbol represents the number of closest neighbors of a newly categorized unknown variable. It is used to solve classification and regression problems. For fewer classes, this has worked out very flawlessly. However, CNN outperforms KNN and SVM in classification for a larger number of classes, according to [5].

III. MelikeSardogan [9] applied CNN to identify plant leaf disease. CNN is a form of ANN in which multiple layers are connected and work on pixel data. CNN is useful for identifying plant diseases. Transfer learning is better than a user-defined CNN model. In transfer learning, a pertained model is customized to a different but similar problem. Many good models, like Inception, ResNet, MobileNet, and EfficientNet, have been developed in recent years. [5] EfficientNetB0 outperforms the others for the colored pictures of the leaf dataset.

METHODOLOGY

In this chapter, we describe the general process of implementing algorithmic steps in detail. LFR employs CNN to classify images and recommend a treatment for the disease. It consists of the following steps:

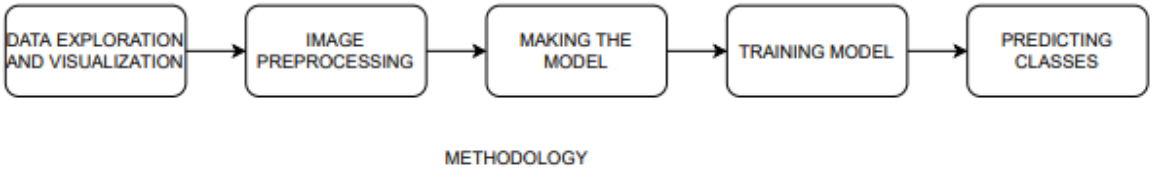

Figure 2 Methodology used in this application

I. Dataset

Visualization of data is done to ensure that the data is properly imported. The model is trained and tested using an open-source labeled dataset. [6] Dataset without augmentation. A key skill is visualizing and exploring data helps to gain a better understanding of it.

Figure 3 Sample images of the dataset

It [6] contains 39 distinct kinds of diseases, of which we have used diseases from the Apple, Potato, and Tomato diseases. It contains 17 classes of color images with dimensions of 256 x 256 pixels (RGB). There are 23483 images in total. The dataset is noise-free and has the same background for all images.

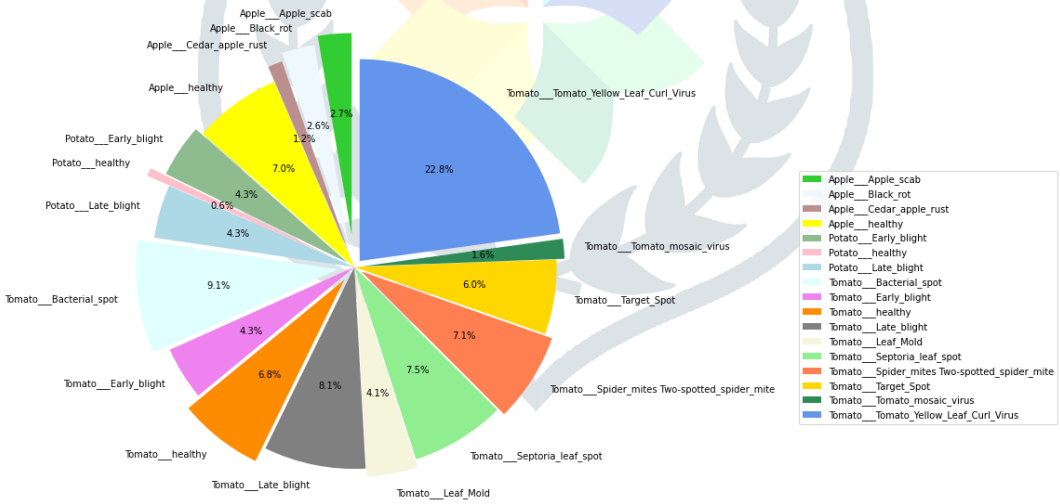

Figure 4 Size of each class in the dataset

The dataset is divided into three sections: train (80%), validation (10%), and test (10%). Images are resized to the required 224 x 224-pixel size while importing. Training with Augmented images improves the Model's accuracy.

II. Image pre- processing

In this step, we alter the images before training the model; this process of augmenting the images is called image pre-processing. This includes, but is not limited to, size, shape, and color correction. Augmenting is a technique used in images to generate multiple versions of the same content in order to present a model in a variety of training examples. We have performed resizing, random rotation, and random zoom in this project.

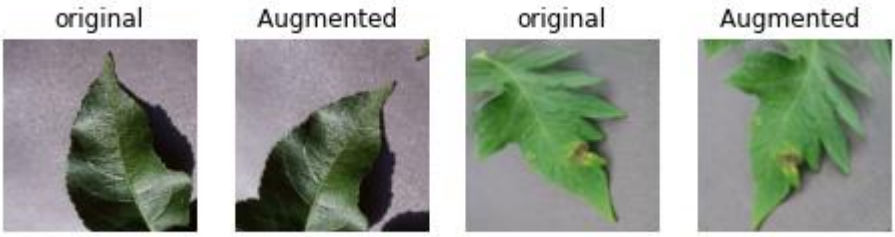

Figure 5 Data Augmentation

III. Making and Training Model

Machine learning is divided into several categories, one of which is deep learning. Deep learning is divided into several categories, one of which is CNN. Transfer learning is used in this project. Transfer learning is the process of taking the relevant portions of a pre-trained learning model and applying them to a new problem that is similar to the previous one. The pre-trained CNN model is customized with the required Input, Output. On a data set of leaf diseases, Sk Mahmudul Hassan [5] employed Inception V3, InceptionResNetV2, MobileNetV2, and EfficientNetB0. As a result, EfficientNetB0 outperformed the others in colored leaf images across all Dataset splits.

Stage	Operator	Stride	#Channels	#Layers
0	Conv3x3	2	24	1
1	Fused-MBConv1, k3x3	1	24	2
2	Fused-MBConv4, k3x3	2	48	4
3	Fused-MBConv4, k3x3	2	64	4
4	MBConv4, k3x3, SE0.25	2	128	6
5	MBConv6, k3x3, SE0.25	1	160	9
6	MBConv6, k3x3, SE0.25	2	272	15
7	Conv1x1 & Pooling & FC	-	1792	1

Figure 6 Architecture of EfficientNetV2B0

It is noted for its high-quality image classification and speed. They are well-known for their scaling approach, which allows them to train considerably more rapidly than other networks. EfficientNetV2 was published by Google recently. It has a significant increase in terms of training speed and accuracy.

EfficientNetV2 is a new convolutional network family with quicker training rates and more parameter options than earlier models. To enhance training speed and parameter capabilities, this was created using a blend of training-aware Neural Architecture Discovery and scaling. In the Flower/Car/CIFAR and ImageNet datasets, EfficientNetV2 has outperformed earlier models thanks to progressive learning. Our EfficientNetV2 obtained 87.3 percent Top-1 accuracy in ImageNet ILSVRC2012 after pre-training on the same ImageNet21k, outperforming the latest ViT with 2.0 percent accuracy while training 5x-11x faster with the same computer resources [7].

In the opening layers, EfficientNetV2 makes extensive use of both MBConv and the newly introduced Fuse-MB Conv. For MBConv, EfficientNetV2 favors smaller expansion ratios since they can result in lower memory access overhead.

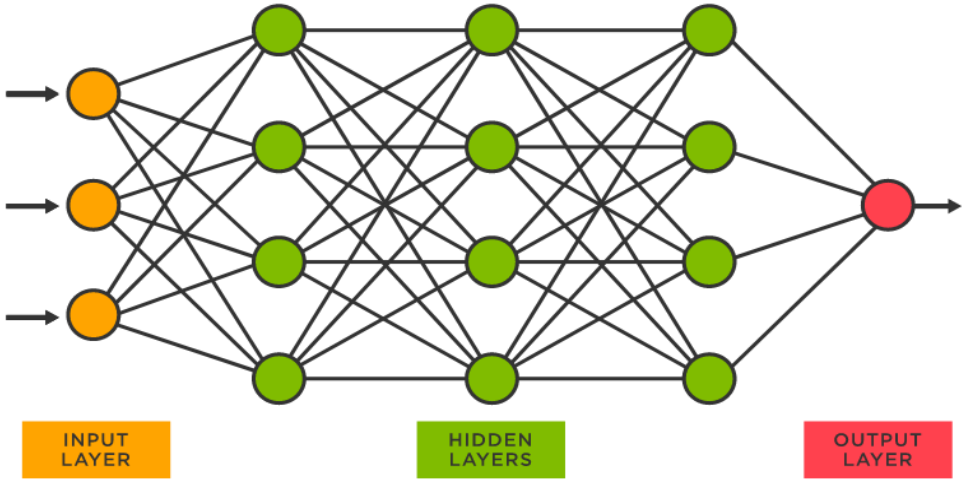

Figure 7 CNN architecture

The input size of EfficientNetV2B0 is 224 × 224 pixels. So, once the 256 × 256 photos have been converted, they are used to train the model. We loaded the pretrained EfficientNetV2B0 and removed the input and output layers in this application [8]. Then, based on our dataset, we adjusted the input-output.

We applied the Adam optimizer, Sparse categorical Cross entropy for loss, and accuracy metrics in this paper. Adam is a gradient descent optimization method and algorithm. When dealing with a large problem with a lot of data or parameters, this strategy works well. It is more efficient and takes less memory.

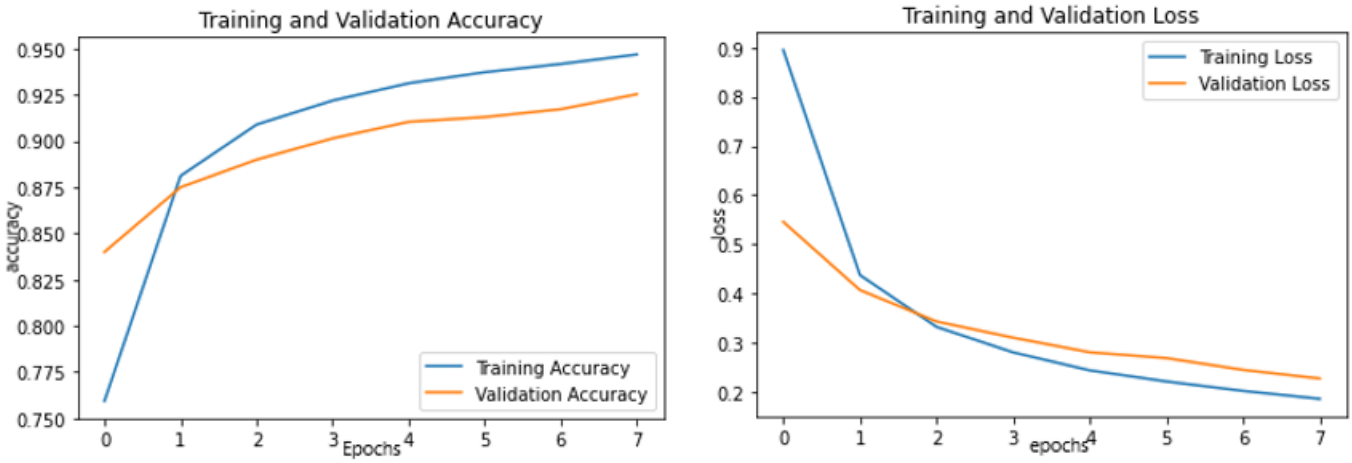

Figure 8 Accuracy vs. Epochs and loss vs. Epochs

The model's accuracy improved greatly during the epochs, while the model's loss declined substantially. The graphs above show the substantial development made over the epochs. The number of correctly predicted photos divided by the total number of images is the accuracy. The training accuracy after each epoch is the accuracy of the training dataset. The accuracy of the validation dataset after each epoch is known as validation accuracy.

IV. Testing

We must test the model with test data to see if any anomalies exist, such as the model being overfitted or underfitting. We need to test the model's classification on a test dataset to verify its performance. Input an image and let the model predict its disease name, which you can then compare to the image's actual disease name. We can use a formula to calculate accuracy.

*Accuracy (%) = ((No. of correctly Predicted) / (Total no of leaves in Datasets))*100*

Figure 9 Sample test results

The accuracy is quite high for apples (scab, black rot, healthy), potato(early light), and tomato (yellow leaf curls, leaf mold, healthy). Because there are fewer samples of Tomato spider mites, two-spotted spider mites, and mosaic virus, the accuracy is lower when compared to other classes. The size of each class is plotted in figure 4.

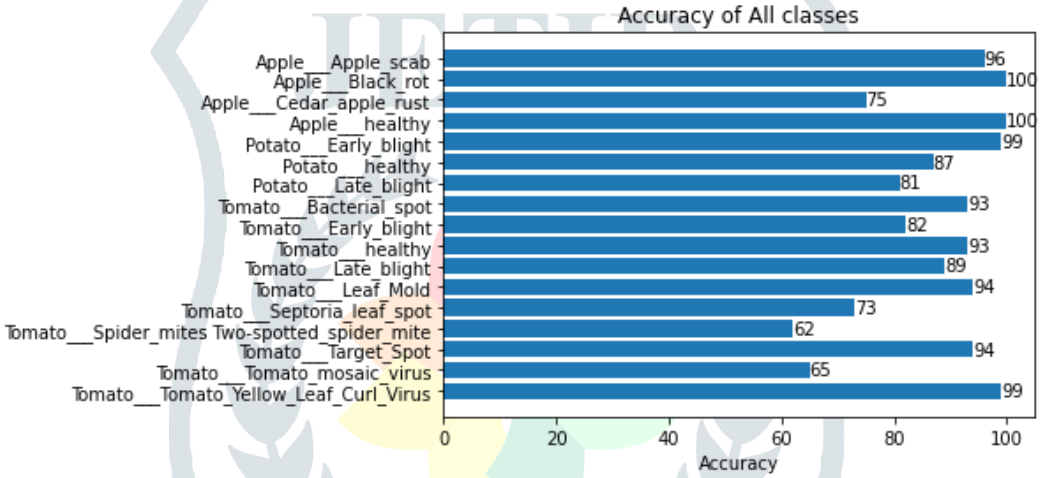

Figure 10Accuracy of each class after training

V. Application

This is a model integrated with Window Application [8]. This application can browse the system files and capture photographs from the webcam. Then, using photos, it predicts disease and proposes a treatment option. This is a minimal user interface. Because most individuals are unaware of the disease, this app recommends a cure and educates them on the cause.

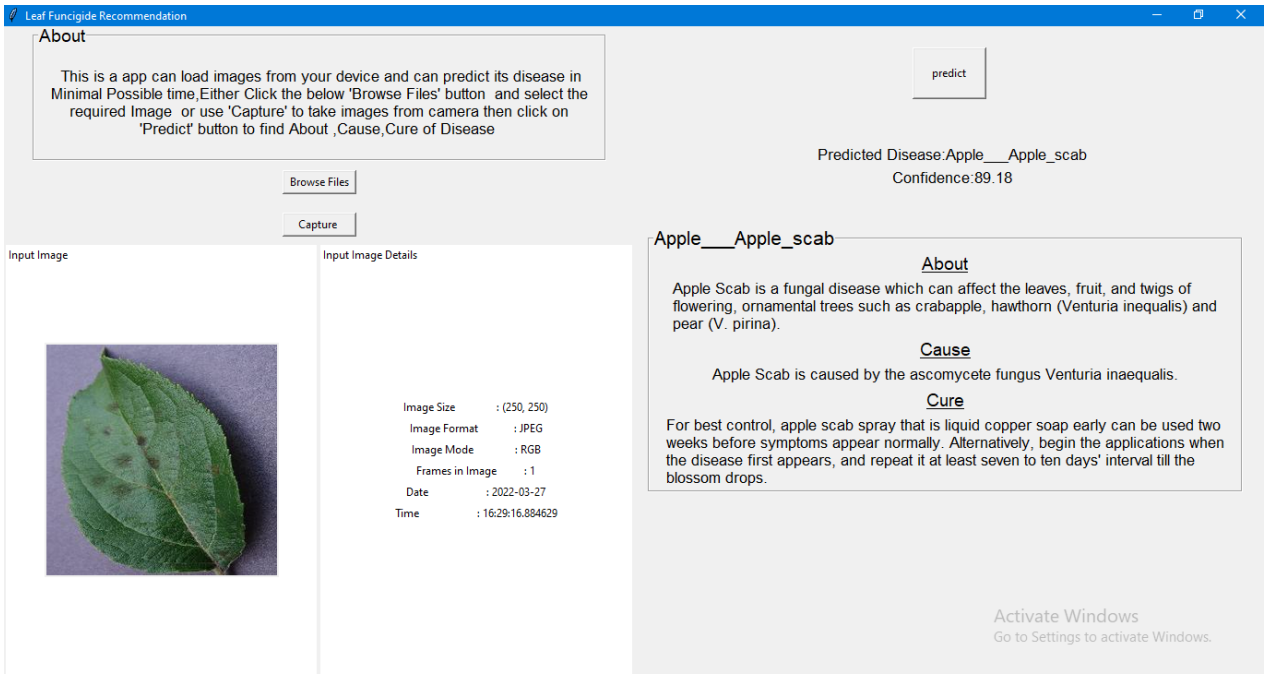

Figure 11Application Graphical User Interface

CONCLUSION

In this paper, we present a graphical user interface (GUI) that may be used to quickly identify plant diseases such as Apples, potatoes, and tomatoes. EfficientNetV2B0, a smaller and faster training model, is employed in this paper. This application aids in the detection of disease, the treatment of disease, and the education of the disease's cause. It is required that the correct dosage and fungicide be used. As a result, the crop will emit less pollution and produce healthier food. This application can also be expanded and combined with drones, reducing human requirements. It can also save time while covering a large area of crop, and regular diagnosis helps in the early detection of diseases. This can also be advanced to find all the diseases in the crop and find the shortest path to spray the fungicide to the crop without overusing the fungicide on healthy plants. Else we can directly attach the fungicide pipes to drones and spray whenever it encounters a leaf disease. This application predicts faster and, more precisely, reduces the use of ineffective pesticides in the fields.

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