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Smart Agriculture: Improving Crop Health

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Abstract- Pest damage to plants and crops has an impact on the nation's agricultural output. In most cases, farmers or professionals watch the plants carefully for signs of illness. However, this procedure is frequently time-consuming, costly, and unreliable. Results from automatic detection employing image processing methods are quick and precise. This study uses deep convolutional networks to establish a new method for developing illness detection models that is backed by leaf image categorization. The area of precision agriculture has a possibility to grow and improve the practice of precise plant protection as well as the market for computer vision applications. A quick and simple system is made possible by the approach utilized and a wholly original manner of training.

Indexed Terms- Plant Disease Detection, Machine Learning, Image Processing, Deep Learning, Convolutional Neural Network

I. INTRODUCTION

Sustainable agricultural issues are directly related to the challenge of effective disease prevention. Inexperienced pesticide use can result in microorganisms developing long-term resistance to antibodies, greatly weakening their ability to defend themselves. One of the foundational elements of precision agriculture is the prompt and precise identification of plant diseases. In this changing climate, it is essential to eliminate needless waste of money and other resources in order to achieve healthy production.

There are several methods for identifying plant disorders. In cases where there are no obvious indications of a disease or when it is too late to take action, a sophisticated study is required. However, since most illnesses have subtle visual symptoms, the primary method used in practice for disease identification is an eye inspection performed by a qualified specialist. A plant pathologist has to be skilled in observation in order to recognise distinctive signs and make an accurate disease diagnosis. Variations in the symptoms displayed by sick plants may result in an incorrect diagnosis since casual gardeners and crafters may have more trouble identifying it than experienced plant pathologists.

As a confirmation method in disease diagnosis, an automatic system can be created to help identify plant illnesses by the look of the plant and visual symptoms detected by the system would be very beneficial to both inexperienced gardeners and qualified specialists in order to recognise distinctive signs and make an accurate disease diagnosis. Variations in the symptoms displayed by sick plants may result in an incorrect diagnosis since casual gardeners and crafters may have more trouble identifying it than experienced plant pathologists.[1]

This paper discusses the issue of plant disease detection using CNN and the samples of different diseases that can be detected by this technique.

The final application of this paper is for plant disease detection. It describes a method for predicting plant diseases by converting an image into a binary image with help from image classification models or object models such as those from convolutional neural networks (CNN). More specifically, the paper discusses how blocks of pixels are converted into classifications with high accuracy rates.

Fig1.Converting an image into a binary image

II. PROPOSED METHOD

The CNN algorithm is used in the proposed system to identify illness in plant leaves because, given [2] appropriate data, it may provide the highest level of accuracy.

Overdoses and other disease-related problems can affect plants in different ways. There are many reasons, which may be distinguished by how they affect plants, disruptions brought on by environmental factors like temperature, humidity, too much or too little food, light, and the most prevalent diseases including bacterial, viral, and fungal illnesses.

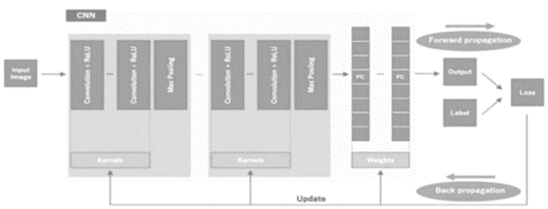

Fig2.Basic Structure of CNN

A. Dataset

Plant Village Dataset is employed.[4] The healthy and sick leaf photos in the Plant Village collection are grouped by species and illness. We attempted to predict the class of illnesses by analyzing more than 3000 photos of plant leaves with scattered labels from 3 potato classes initially. The image is reduced in size to 256 x 256 pixels, and this compressed image is then optimized and model predictions are made.

Fig2.Image Dataset

B. Processing

A powerful image classifier must incorporate image augmentation. Even while datasets may have hundreds to a few thousand training samples, the variety may not be sufficient to create a reliable model. The many picture enhancement choices include resizing the image, rotating it at different angles, and flipping it vertically or horizontally. It is discovered that each image in the Plant Village collection is 256×256 pixels in size. The Keras [3] deep-learning framework is used for data processing and picture enhancement.

The augmentation options used for training are Rotation, Brightness, contrast and Flipping during training

C. System Overview

1. Input images are first created by an Android device or uploaded to our web application by users.

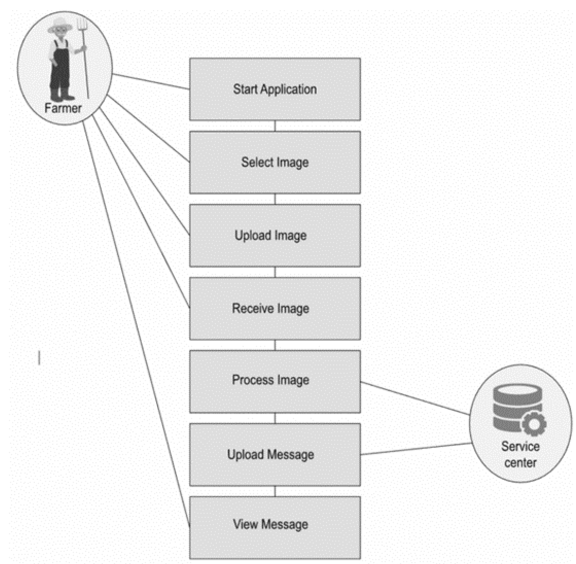

Fig3.Overview

III. EXPERIMENTATION

At First an array is created from each picture.[5] The input file received is scaled from [0, 255] (the image's least and most common RGB values) to the range [0, 1]

The dataset was then divided into 20% for testing photos and 80% for training images. Objects that conduct random rotations, motions, inversions, civilizations, and sections of our picture library are formed as image generators.

Layer (type)	Output Shape	Param #
sequential (Sequential)	(32, 256, 256, 3)	0
sequential_1 (Sequential)	(None, 256, 256, 3)	0
conv2d (Conv2D)	(None, 254, 254, 32)	896
max_pooling2d (MaxPooling2D)	(None, 127, 127, 32)	0
conv2d_1 (Conv2D)	(None, 125, 125, 64)	18496
max_pooling2d_1 (MaxPooling 2D)	(None, 62, 62, 64)	0
conv2d_2 (Conv2D)	(None, 60, 60, 64)	36928
max_pooling2d_2 (MaxPooling 2D)	(None, 30, 30, 64)	0
conv2d_3 (Conv2D)	(None, 28, 28, 64)	36928
max_pooling2d_3 (MaxPooling 2D)	(None, 14, 14, 64)	0
conv2d_4 (Conv2D)	(None, 12, 12, 64)	36928
max_pooling2d_4 (MaxPooling 2D)	(None, 6, 6, 64)	0
flatten (Flatten)	(None, 2304)	0
dense (Dense)	(None, 64)	147520
dense_1 (Dense)	(None, 3)	195

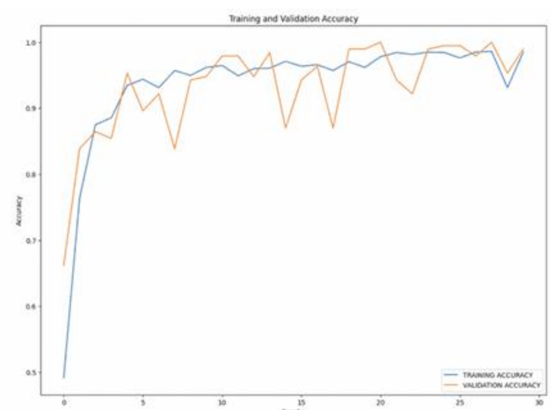

Fig 4. Various Convolutional Layers Output

For this model, I employed Adam's Hard Optimizer. The Primary Step is to add data, train-test data, and the number of training epochs. In this project, I chose the number of epochs to be 30

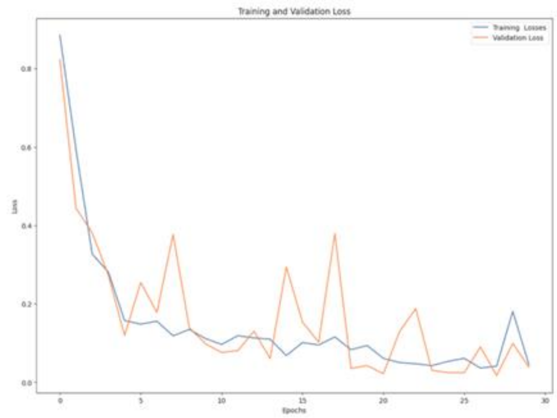

Fig 5. Training and Validation Accuracy

IV. RESULT AND ANALYSIS

In spite of the fact that we lacked a large dataset and access to strong processors,[6] the findings above demonstrate that CNN functions well and can accurately diagnose plant disease. With 98.6% accuracy, we were able to identify the condition in the photos.

Fig 6. Web App Preview

We made the user interface of our online application as easy as we could so that everyone, regardless of age or level of awareness, could utilize the web app to detect the disease

CONCLUSION

Crop protection in farming is a difficult task. [7] This is reliant on in-depth familiarity with the crop being grown and any potential pests, pathogens, and weeds. Our method uses photos of healthy or sick plant leaves to detect plant illnesses using a specific deep learning model built on a particular architectural convolution network.

In this farmer needs no prior knowledge about how to detect different crop diseases. Because the web app is so user-friendly, people of any age may participate and immediately begin learning new things. However, there is still a great desire to conduct more research and produce results with more accuracy

FUTURE WORK

We would like to add many more features. Currently, the Web Application only contains a small number of features. We will be adding various new features like E-commerce Integration and Gathering more Dataset can be used to achieve higher accuracy in Future.

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