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Plant Disease Detection Using Deep Neural Network

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ABSTRACT

Agriculture has a vital role in human life. Almost 60% of the population is involved in agriculture in some way, either directly or indirectly. Farmers are not interested in expanding their agricultural production day by day because there are no technologies in the old system to identify diseases in diverse crops in an agricultural setting. Crop diseases have an impact on their particular species' growth, hence early detection is essential. Many Machine Learning (ML) models have been used to detect and classify crop illnesses, but recent breakthroughs in a subset of ML known as Deep Learning (DL) look to hold a lot of promise in terms of enhanced accuracy. To effectively and precisely identify and characterize crop disease signs, the suggested method employs a convolutional neural network and a Deep Neural Network. These solutions are also evaluated using a variety of efficiency indicators. This article goes through the DL models that are used to depict crop diseases in detail. Furthermore, various research gaps have been found, allowing for increased transparency in detecting plant illnesses even before symptoms appear. The suggested methodology seeks to create a plant leaf disease detection strategy based on convolutional neural networks.

Keywords - **OpenCV, Plant Disease Detection, Convolution Neural Network, Deep Learning..**

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I. INTRODUCTION

The People can now offer appropriate nourishment and food to meet the needs of the world's rising population thanks to advancements in technology. If we talk about India indisputably, 70% of the population is directly or indirectly linked to the cultivating territory, which remains the country's largest region. If we look at the big picture, According to research, overall yield creation might increase by at least half by 2050 by putting more emphasis on the inside and out pushed and cultivating sectors. The majority of farmers are impoverished and have little interest in improvement, which may result in troubles for more than half of them due to pets and plant diseases. Vegetables and fruits are the most prevalent and important agricultural products. The high material concentration of designed pesticides results in a hostile influence on the environment in the soil, air, water, and, astonishingly, in human bodies.

Plant illnesses are currently unable to define using the traditional method of visual assessment in humans. Computer vision models have advanced to the point where they can now provide quick, standardized, and accurate responses to these issues. During the preparation process, classifiers can also be submitted as attachments. All you need is a web connection and a smartphone with a camera. “I Naturalist” and “Plant Snap,” two well-known business applications, demonstrate how this is feasible. Both apps are great at sharing talents with clients and creating user-friendly online social groups.

Figure 1. Disease Plant Leaves

Deep Learning has recently achieved outstanding results in disciplines such as image recognition, speech recognition, and natural language processing. The Convocational Neural Network has produced excellent results in the problem of Plant Disease Detection. The best approach for

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Object Recognition is the Convocational Neural Network. We look at neural architecture, namely faster Region-Based Convolutional Neural Networks (Faster R-CNN), Region-based Convolutional Neural Networks (R-FCN), and single-shot Multi box detectors (SSD). Depending on the application, each Neural Architecture should be able to be combined with any feature exactor. For models to work accurately, data pre-processing is critical. Many infections (viral or fungal) can be difficult to distinguish because their symptoms overlap.

This study is separated into numerous different sub-methods based on the processing characteristics of each type of method, as shown in Fig. 2.

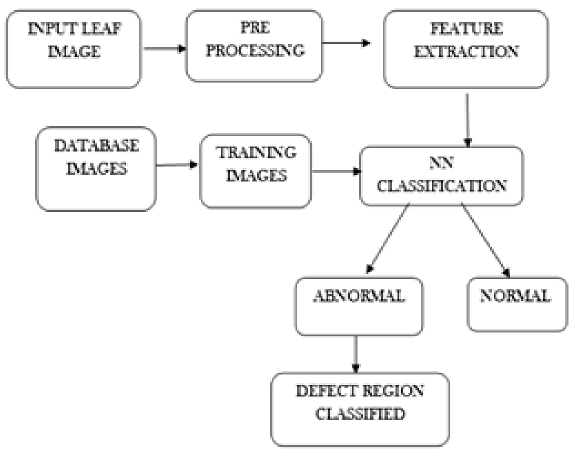

Figure 2. Framework of plant diseases and pests detection methods based on deep learning

Neural network using convolutions CNNs, also known as convolutional neural networks, have a sophisticated network topology and can execute convolutional operations. The input layer, convolution layer, pooling layer, full connection layer, and output layer make up the convolutional neural network model, as shown in Figure 3. The convolution layer and the pooling layer alternate numerous times in one model, and no full connection is necessary when the convolution layer's neurons are connected to the pooling layer's neurons. In the realm of deep learning, CNN is a popular model.

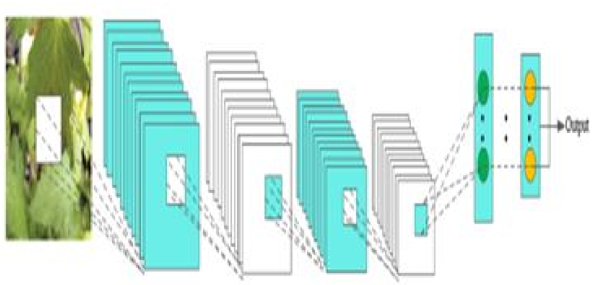

Figure 3. The basic structure of CNN.

II. Literature Review

Thenmozhi et al. [5] suggested a useful deep CNN model that uses transfer learning to fine-tune the pre-training model. On three public bug datasets, insect species were categorized with accuracy of 96.75 percent, 97.47 percent, and 95.97 percent, respectively.

Fang et al. [6] ResNet50 was used by to detect plant diseases and pests. The Adam optimization approach was utilized to detect the leaf disease grade, and the focus loss function was used instead of the normal cross-entropy loss function. The accuracy was 95.61 percent.

Nagasubramanian et al. [7] employed a three-dimensional deep convolution neural network (DCNN) and salience map visualisation method to distinguish between healthy and infected soybean stem rot samples, with a classification accuracy of 95.73 percent.

Picon et al. [8] suggested a CNN architecture for identifying 17 illnesses in five crops that smoothly combines context metadata and allows for the training of a single multi-crop model. The model can help you achieve the following objectives: (a) becomes more abundant and is not affected by different illnesses in which different crops have similar symptoms; (b) smoothly integrates context to perform crop conditional disease classification; (c) is not affected by different diseases in which different crops have similar symptoms. Experiments reveal that the suggested model solves the data imbalance problem, with an average balanced accuracy of 0.98, which is better than existing methods and removes 71 percent of classifier errors.

Tianjiao et al. [9] built a framework for characteristics automatic learning, feature fusion, recognition, and location regression calculation of plant diseases and pest's species using a CNN classification network based on sliding window, and the recognition rate of 38 common symptoms in the field was 50–90%.

Dechant et al. [10] trained CNN to create a heat map showing the probability of infection in each region in maize disease images, and then utilized these heat maps to classify the entire image, splitting each image into containing or not containing infected leaves. It takes roughly 2 minutes (1.6 GB of RAM) to generate a heat map for an image and less than a second to classify a set of three heat maps at runtime (800 MB of memory). Experiments reveal that on the test dataset, the accuracy is 96.7 percent.

Wiesner-Hanks et al. [11] proposed with an accuracy rate of 99.79 percent, employed the heat map approach to generate correct contour regions of maize illnesses. The model can accurately portray lesions as small as millimeter scale from images taken by UAVs. This is the most accurate scale of aerial plant disease detection yet achieved.

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Prakash Kanade et al. [12] this paper presented an outline of altered assortments of plant illnesses and different gathering measures in AI utilized in various plant leaves for brand name infections. The trial results demonstrate that, even with an exactness of 96.7 percent, the utilization of adjusted AI techniques could be successfully utilized for the grouping of plant leaf illnesses. This technique would be gainful for ranchers to maintain a strategic distance from crop harm, the absence of food creation in the public arena and the misuse of cash on farming items, for example, pesticides, and so forth.

III. Problem Statement

The first paragraph under each heading or subheading should be flush left, and subsequent paragraphs should have a five-space indentation. A colon is inserted before an equation is presented, but there is no punctuation following the equation. All equations are numbered and referred to in the text solely by a number enclosed in a round bracket (i.e., (3) reads as "equation 3"). Ensure that any miscellaneous numbering system you use in your paper cannot be confused with a reference [4] or an equation (3) designation.

IV. Proposed System

Plants are susceptible to a wide range of diseases and convulsions. There are a variety of causes that can be classified based on their impact on plants, including disturbances caused by environmental factors such as temperature, humidity, excess or insufficient food, light, and the most prevalent diseases such as bacterial, viral, and fungal infections. We employ the CNN algorithm in the suggested system to identify disease in plant leaves since the maximum accuracy can be attained with CNN if the data is good.

Dataset

Plant Village Dataset is what we use. There are 54303 healthy and diseased leaf photos in the Plant Village dataset, which are split into 38 groups based on species and disease. We looked at over 50,000 photos of plant leaves with labels distributed over 38 classes to see if we could determine which disease class they belonged to. On this compressed image, we do optimization and model predictions after resizing it to 256 x 256 pixels.

Table I. Leaf Classification

Leaf Class	Link
Plant Disease Symptoms	www.digipathos-rep.cnptia.embrapa.br
Rice Leaf Diseases	www.archive.ics.uci.edu /ml/datasets/Rice+Leaf+ Diseases
insects from rice, maize, soybean, sugarcane and cotton crops	http://www.nbair.res.in/insectpests/pestsearch.php
apple leaf disease	www.kaggle.com/c/plantpathology-2020-fgvc7
tomato pest images	data.mendeley.com/datasets/s62z6djd2/1
Maize leaf	https://bisque.cyverse.org/client_service/browser?resource=/data_service/dataset
RGB images of healthy and diseased crop leaves	www.kaggle.com/vipoooool/new-plant-disea ses-dataset/
Plant Disease Symptoms	www.digipathos-rep.cnptia.embrapa.br
high quality JPG image data of rice, wheat and maize	www.icgroupcas.cn/website_bchtk/index.html


(A) Apple Healthy


(B) Apple Scab


(C) Strawberry Healthy


(D) Strawberry Leaf Scorch


(E) Tomato Healthy


(F) Tomato Leaf Mold

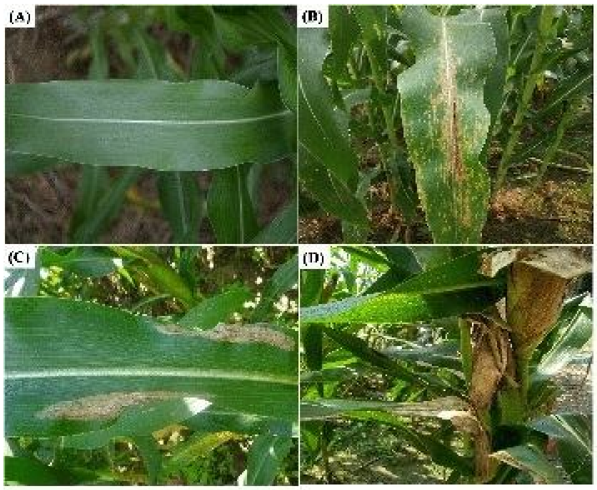

Figure 4. Images from the Dataset

V. Implementation

Image Enhancement:
Image enhancement is the process of changing digital images such that the effects are more suitable for display or subsequent image processing. To improve an image, you can do any of the following:

- Histogram Equalization.
- Noise removal using filters.
- Unsharp mask filtering.
- Decorrelation stretch etc.

Image Segmentations:
Image segmentation is the process of dividing a digital image into several segments (sets of pixels, also known as image objects). Picture segmentation divides an image into numerous pieces and analyses each section separately, making image identification and analysis easier. Color, texture, and intensity are all traits shared by all of the segments.

Image analysis:
Image segmentation is performed to locate the region of interest in this stage. Region-based segmentation is a segmentation technique that uses the color of the leaf to discriminate between healthy and diseased plant leaf sections. 5.6 Feature Extraction: In machine learning, feature extraction is a part of the dimensionally reduction method, which divides and reduces a huge set of raw data into smaller classes. This stage is crucial when we have a huge volume of data and need to reduce the number of resources while avoiding errors. As a result, by selecting and merging variables into functions, function extraction aids in the extraction of the best feature from big data sets.

Disease Classifications:
It's a way for detecting plant illness using our qualified deep learning model. To photograph the contaminated plant's leaf, use a digital camera or an analogous equipment. The image was scanned with Opencv. Then it determines the plant's species. After discovering the ailment, it determines what type of sickness the plant has.

VI. Result and Discussion

The analysis tools are based on image classification, in which each studied image is assigned a class or category name as shown in Figure 5.

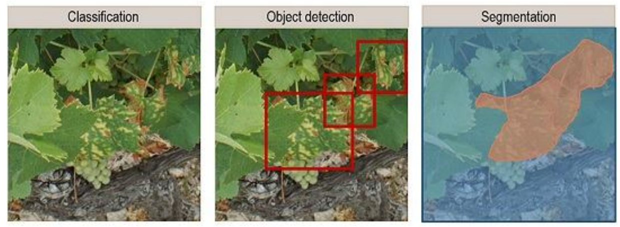

Figure 5. Expected output examples

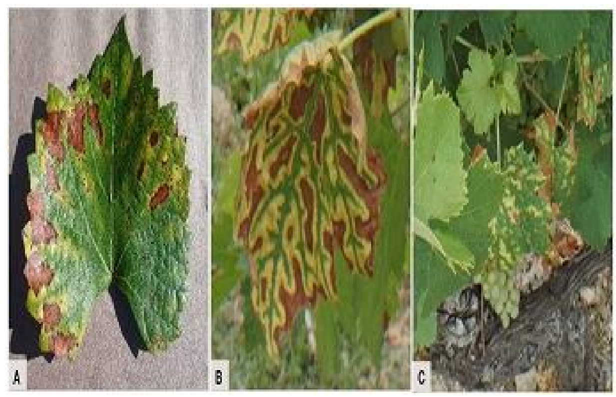

Figure 6. Typology of image complexity found in the datasets

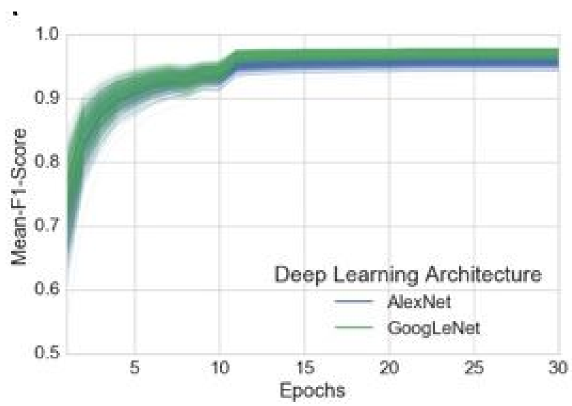

Figure 7. Comparison of progression of mean

We trained a model on photos of plant leaves using the deep convolutional neural network architecture, with the purpose of distinguishing both crop species and the presence and identification of illness on images that the model had never seen previously. This goal was accomplished within the PlantVillage data set of 54,306 photos encompassing 38 classes of 14 crop species and 26 diseases (or lack thereof), as evidenced by the top accuracy of 99.35 percent. Thus, in 993 out of 1000 photos, the model properly classifies crop and disease from 38 potential classes without any feature engineering. Importantly, while the model's training takes a long time (several hours on a high-performance GPU cluster computer), the classification is quick (less than a second on a CPU), and so can be simply implemented on a smartphone. This paves the way for widespread use of smartphone-assisted crop disease diagnostics on a global scale.

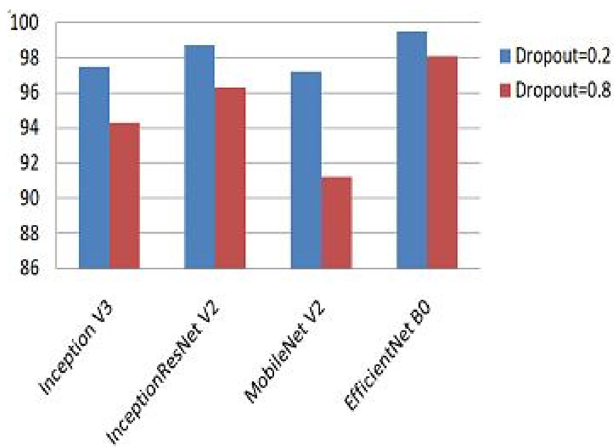

Figure 8. Performance accuracy with different dropout values.

Figure 8 depicts performance accuracy in relation to the network's various dropout settings.

VII. Conclusion

Crop protection in organic farming is a difficult undertaking. This requires a thorough understanding of the crop being farmed as well as potential pests, diseases, and weeds. A new deep learning model based on a special architectural convolution network has been constructed in our system to detect plant illnesses using photos of healthy or diseased plant leaves. The aforementioned system can be expanded to a real-time video entry system, allowing for unattended plant care. An intelligent system that treats diagnosed diseases is another feature that can be introduced to various systems. Plant disease management has been shown in studies to enhance yields by up to 50%. Our method is centered on employing a deep-learning-based transfer-learning methodology to identify illnesses. In the inception block, instead of utilizing ordinary convolution, we employed depth wise separable convolution, which drastically decreased the amount of parameters. The InceptionResNetV2 model was utilized to leverage both the inception and residual network connection layers. Because the model uses fewer parameters, it is more accurate and takes less time to train than the original architecture.

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