Plant Disease Detection using Convolutional Neural Network

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Abstract:

Plant diseases are responsible for global economic losses because of degradation in the quality and productivity of plants. Therefore, plant disease detection has become a significant area of research for agricultural scientists. Diseases can also be so bad that there is no grain harvest.

Thus, the automatic detection and diagnosis of plant diseases are highly desired in agricultural information. Many strategies have also been offered for handling this job, where deep learning is becoming the dominant method because of the fantastic performance.

Keyword:

Deep Learning, Convolutional Neural Network, Plant Disease Detection

Introduction:

Farmers who grow the plant face a lot of economic losses yearly because of various plant diseases. Many types of illness occur on the plant.Example in potato plants there are two common types of illness that is early blight and late blight.

A fungus causes early blight and late blight is caused by a specific microorganism and if a farmer can detect these diseases early and apply appropriate treatment then it can solve a lot of waste and prevent the economic loss of the treatment for early blight and late blight are a little different so it’s essential that you accurately identify what kind of disease is there in the plant. So, we have to build a mobile an application that we can give to a farmer. And farmers all they need to do is go to their farm and take a picture of the plant and the mobile application will tell them whether the potato plant is healthy or it has one of these diseases and behind the scene, it will be using deep learning and convolutional neural network.

The Deep CNN model is trained using an open dataset with twenty-threedifferent classes of plant leaves and background images. As we are using data augmentation can increase the performance of the model. This proposed model was trained using different training epochs, batch sizes, and dropouts. Compared with popular transfer learning approaches, the proposed model performs better using the validation data. The accuracy of the proposed work is greater than the accuracy of traditional machine learning approaches.

The purpose of this work is to assess the effectiveness of training a plant disease classifier using a pre-trained ResNet34 model. The main focus will be on five plant species. Potato, tomato, corn, apple, and strawberry are a few of them. The model will be trained to recognise a small number of diseases or health conditions specific to each species.

The Objective of this research:

- Using a validation and test dataset, evaluate the model's general suitability for categorising illnesses.
- When the model is evaluated with different image sizes and augmentation settings, compare its accuracy.
- Utilize the trained model to build a user-friendly web application.

The requirements of smallholder farmers will be taken into consideration when this research is conducted. Both a smartphone and an internet connection, which are still available in distant areas, are needed for the classifier and the web application. In order to evaluate the model with a range of image sizes and augmentation settings, it will be necessary to acknowledge the limitations of entry-level camera phones.

Literature Review

This paper outlines a method for accurately identifying apple leaf diseases. The deep CNN model is based on AlexNet and is meant to detect four common disorders. The total accuracy of the suggested illness detection model is 97.62 percent, with the parameters reduced by 51,206,928 and improved by 10.83 percent with produced pathological pictures. This research suggests that the deep learning model for disease management may be more accurate and have a faster convergence rate, enhancing disease control.[1]

Sharath D. M. and colleagues developed a Bacterial Blight detection method for Pomegranate plants in 2019 using variables such as colour, mean, homogeneity, SD, variance, correlation, entropy, and edges. Grab cut segmentation was used to segment the image's region of interest and the edges were extracted using the Canny edge detector. The authors have also developed a system to forecast the degree of infection in the fruit. [2]

Konstantinos P. Ferentinos and colleagues-built CNN models were used to identify and treat plant disease identification and treatment. The models were trained using an open collection of 87,848 photos, including 25 kinds of plants in 58 classes of [plant, illness] pairs. The top performing one achieved a success rate of 99.53 percent, making it a valuable early detection tool.[3]

This Paper outlines strategies for extracting the nature of infected leaves and classifying plants Disease using a Convolution Neural Network (CNN). The process is described based on images used for training and pre-treatment testing, image enhancement, and CNN deep and optimizers. This will help to determine the processing method and differentiate between different plant diseases.[4]

Angie K. Reyes et al. (Reyes, Caicedo, and Camargo 2015) developed a deep learning approach with 5 Conv layers and 2 fully connected layers. The CNN is trained using 1.8 million images from ILSVRC 2012 and a finetuning strategy to transfer learned recognition capabilities to the specific challenge of Plant Identification task. The dataset is a combination of images of a plant or part of a green plant taken both under a controlled environment and in the natural environment, achieving an average precision of 0.486.[5]

Proposed System:

To overcome the drawbacks of the current framework, a computer vision-based disease discovery system is proposed to assess the illness of maize plants.

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

A sizable collection of plant leaf photos is needed in order to categorise plant diseases. the New Plant Diseases Datasetdatabase is used to download the pictures.

Block Diagram of Proposed System

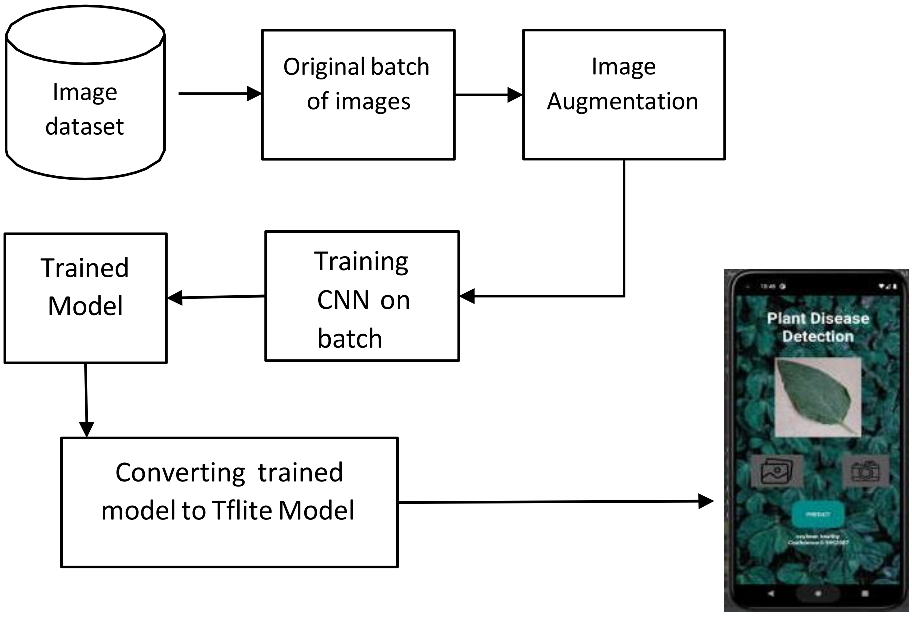

Figure 1

1. Collecting information is the first step. We are use the readily accessible Plant Diseases Dataset.
2. The acquired dataset is pre-processed and enhanced using Keras' pre-processing and Image-data generation API.
3. Convolutional neural network (CNN) model construction for the classification of various plant diseases
4. TensorFlow lite will be used to deploy the developed model to the Android application.

Figure 2

Dataset

For every classification research during the training and testing phases, a suitable and sizable dataset is necessary. The New Plant Diseases Dataset, which includes a variety of plant leaf images and their labels, is where the dataset for the experiment is downloaded fromkaggel. It includes a selection of photos taken in various settings. Downloaded is a collection with 42638 leaf photos divided into 23 classes, including healthy leaves. Table no:1 lists the samples from the dataset for each class.

Table No: 1

No.	Type of Disease	Number
1	Apple___Apple_scab	2016
2	Apple___Black_rot	1987
3	Apple___Cedar_apple_rust	1760
4	Apple___healthy	2008
5	Grape___Black_rot	1888
6	Grape___Esca_(Black_Measles)	1920
7	Grape___Leaf_blight_(Isariopsis_Leaf_Spot)	1722

8	Grape___healthy	1692
9	Potato___Early_blight	1939
10	Potato___Late_blight	1939
11	Potato___healthy	1824
12	Tomato___Bacterial_spot	1702
13	Tomato___Early_blight	1920
14	Tomato___Late_blight	1851
15	Tomato___Leaf_Mold	1882
16	Tomato___Septoria_leaf_spot	1745
17	Tomato___Spider_mites Two-spotted_spider_mite	1741
18	Tomato___Target_Spot	1827
19	Tomato___Tomato_Yellow_Leaf_Curl_Virus	1961
20	Tomato___Tomato_mosaic_virus	1790
21	Tomato___healthy	1926
22	Strawberry___Leaf_scorch	1774
23	Strawberry_healthy	1824
Total		42638

Data Processing and Augmentation

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 image enhancement choices include resizing the image, rotating it at different angles, and flipping it vertically or horizontally.

The amount of pertinent data in a dataset is increased by these augmentations. It has been determined that each image in the new plant disease dataset is 256 × 256 pixels in size. Using the Keras deep-learning frame v ork, data processing and image enhancement are carried out.

The following are th ϵ augmentation choices used for training:

- Rotation - To randomly rotate a practise image at different angles.
- Brightness: By feeding the model photos of varied brightness duri r g training, brightness helps the model adjust to changes in lighting.
- Shear: Change the shearing angle.

Model Building:

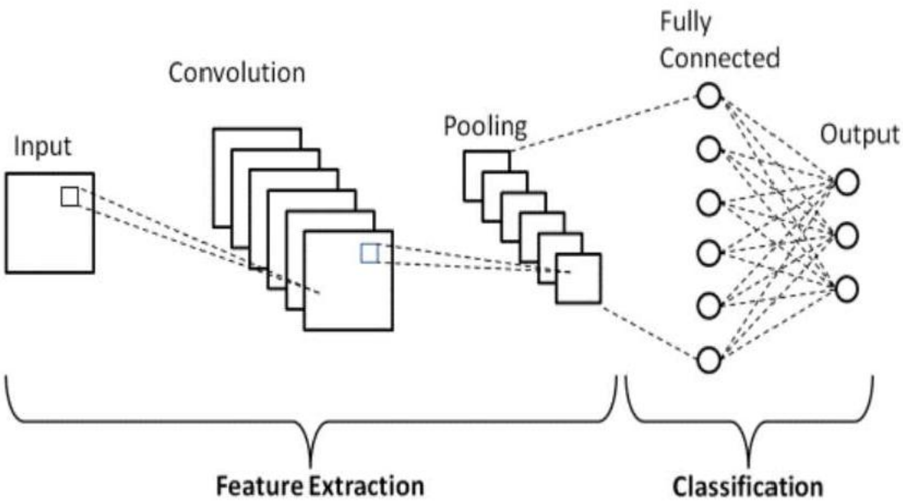

Figure 3

Convolutional layer:

In order to extract features from the input image, a convolution layer alters it. This transformation involves convolving the image with a kernel.

The input data, which are often pictures or feature maps produced by earlier layers, are subjected to a set of learnable filters in a convolutional layer. A series of output feature maps is produced by the filters, which are made up of small matrices of weights that are convolved with the input data.

Pooling layer:

By merging the outputs of neuron clusters at the preceding layerinto a single neuron at the subsequent layer, the pooling layers have the effect of reducing the dimensions of the hidden layer.

Pooling layers are helpful in CNNs because they reduce the spatial dimensions of the feature maps and offer a semblance of translation invariance, which helps to prevent overfitting. Moreover, pooling can aid in drawing attention to the input data's key features, making it simpler for later layers to find more complex features.

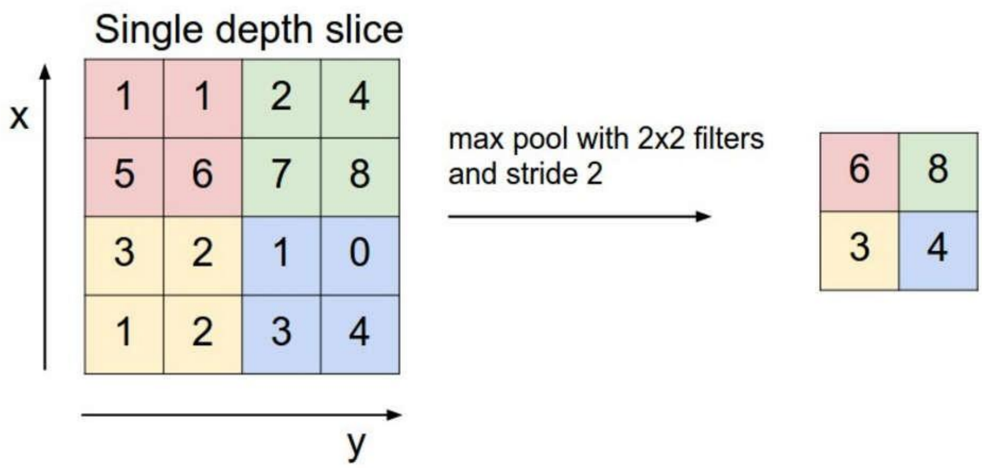

Figure 4

Fully connected layer:

Convolutional Neural Networks (CNNs), which have been demonstrated to be particularly useful in detecting and classifying pictures for computer vision, must include fully connected layers. Convolution and pooling, which divide the image into features and examine each one separately, are the first steps in the CNN process.

Fully connected layers are beneficial in CNNs because they enable the network to learn complex, non-linear mappings between the input data and the output classes. They are often only used at the end of the network because they are computationally expensive and demand a lot of parameters.

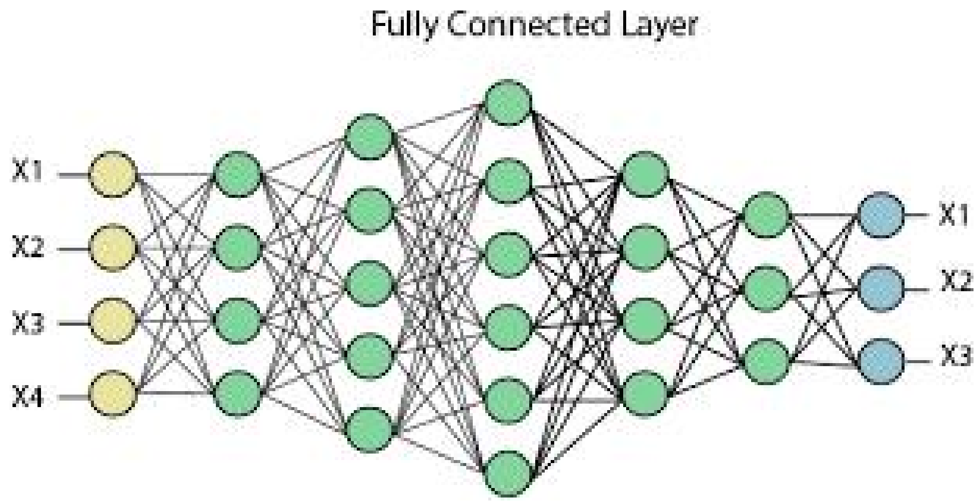

Figure 5

Result:

Early stopping was used to attain a 95.6% accuracy rate when training the model across 50 epochs. The visualisation of training and validation accuracy is shown in Figure 6. Figure 7 displays the outcome of identifying and locating a strawberry plant. A leaf from a healthy plant is on the left, while a sick, infected plant is on the right. Figure 8 depicts the outcome of identifying and locating a potato plant. A leaf from a healthy plant is on the left, while a sick, infected plant is on the right.

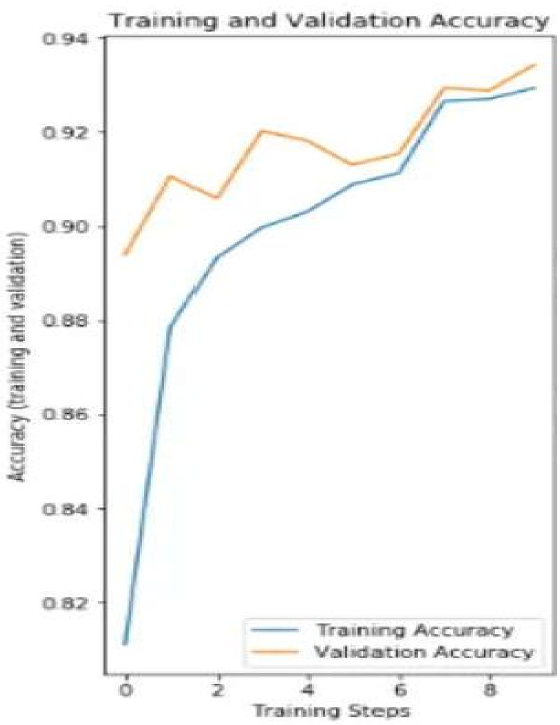

Figure 6

Figure 7

Figure 8

Conclusion and Future work:

This work used deep learning to create an automated system for detecting plant diseases.

This method is built on a straightforward categorization process that makes use of CNN's feature extraction capabilities.

Five different species—apple, tomato, strawberry, soybean, potato—are used to evaluate the proposed approach. This endeavour involved the identification of 23 classes of plants. Working with Keras' image data generator API was successful for us. We were able to do image-processing operations as a result.

In this work, we examine transfer learning of the deep convolutional neural networks for the identification of plant leaf diseases and contemplate using the pre-trained model learned from the typical enormous datasets, and then transfer to the specific task trained by our data.

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