IJARSCT

ISSN (Online) 2581-9429

International Journal of Advanced Research in Science, Communication and Technology (IJARSCT)

Impact Factor: 6.252

Volume 2, Issue 1, May 2022

Performance Analysis of Plant Leaf Disease Detection Using Machine Learning

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Abstract: *There is some most extensively planted vegetable crop in India's agricultural lands. Although the tropical environment is favorable for its growth, specific climatic conditions and other variables influence plant growth. In addition to these environmental circumstances and natural disasters, plant disease is a severe agricultural production issue that results in economic loss. Therefore, early illness detection can provide better outcomes than current detection algorithms [2]. As a result, deep learning approaches based on computer vision might be used to detect diseases early. This study thoroughly examines the disease categorization and detection strategies used to identify plant leaf diseases. The pros and limitations of the approaches provided are also discussed in this study. Finally, employing hybrid deep-learning architecture, this research provides an early disease detection approach for detecting plant leaf disease [1].*

Keywords: Artificial Intelligence, Convolutional Neural Network (CNN), deep learning, leaf disease, tomato leaf, and multiclass classification.

I. Introduction

Precision farming is the next step in the evolution of agriculture. Precision agriculture may boost agricultural output by combining science and technology. Precision farming also entails reducing pesticides and illnesses by accurately calculating the number of pesticides needed [3]. Precision farming has improved several agriculture sectors as it transitions from conventional ways to new approaches. Precision farming's only objective is to obtain real-time data to boost agricultural yield and maintain crop quality [4].

Agriculture is much more than just a means of feeding the world's growing population. Plant diseases have also cost agricultural and forestry businesses a lot of money. As a result, early identification and diagnosis of plant diseases are crucial to take fast action. A variety of methods can be used to identify sickness in plants. On the other hand, certain illnesses are difficult to detect early on [5]. Therefore, they will have to wait a little longer to figure out what is going on. Advanced analysis, which is often done with powerful microscopes, is necessary under these conditions. Furthermore, diseases wreak havoc on a plant's overall health, slowing its development. Unfortunately, a plethora of plant diseases is wreaking havoc on the leaves of the crop. The proposed study's primary objective is to find a solution to the problem of identifying crop leaf disease using the most straightforward technique feasible while utilizing the fewest computer resources necessary to achieve results comparable to state-of-the-art alternatives. In addition, to assist in classifying input photos into sickness classifications, automatic feature extraction is applied. Consequently, the suggested system attained an average accuracy of 94%-95%, demonstrating the neural network approach's viability even under challenging scenarios [4].

Sensors and remote sensing, mapping and surveying, high-precision positioning systems, variable rates, the global navigation satellite system, automated steering systems mapping, computer-based applications, and other technologies are all used in precision agriculture [2]. In addition, precision agricultural concepts based on infrared variation analysis and treatment is also cutting-edge technologies. This examination utilizes a more modest adaptation of the convolutional neural organization model to recognize and analyze messes in tomato leaves.

In other cases, the signals can only be detected in non-visible electromagnetic spectrum areas. This research aims to develop a user-friendly method that will aid farmers in recognizing tomato plant issues without having to consult an expert. We first obtain a picture from the Kaggle dataset, from which we extract characteristics. Then, to remove the attributes, we employ picture conversion and scaling. Finally, to diagnose diseases, the transfer learning model will be used [6].

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Figure 1: Ill leaf

1.1 Image Processing in Precision Agriculture

Precision agriculture uses deep learning techniques, and its approach to crop protection effectively boosts crop development. Image analysis may be used to detect the sick leaf, measure and locate the damaged area's border to identify the item appropriately. This study develops an improved deep learning system for determining the state of a tomato crop based on a photo of its leaves [7].

We all know that the human brain recognizes images far faster than a computer. However, the era has changed with the introduction of Machine Learning. High performance on image identification tasks may be ensured using the model, deep convolution neural network, which can surpass human performance in several domains [5]. By certifying their work against Image Net, researchers have achieved advances in the field of visual recognition.

1.2 Symptoms of Leaf Disease

The plant's color, shape, and function may vary as it responds to the illness. We'll go through the signs and symptoms of these illnesses, as well as what to check for if your plant's development appears to be slow. The appropriate classification and diagnosis of leaf diseases are crucial for reducing agricultural losses. Different plant leaves transmit various diseases and show other symptoms [2].

A. Leaf Bacterial Spot

Bacterial leaf spot is caused by four species of Xanthomonas. It infects all varieties of crop leaf and in the Midwest it causes moderate to severe damage on tomato fruit making then non-marketable due to quality issues. Symptoms include leaf lesions with yellowing and large crusty spots on the fruit.

B. Leaf Mold

Production of tomatoes under high tunnel and plastic has increased significantly over the last few years in part due to consumers demand for “local” produce. Even though growing under these conditions can reduce the occurrence of some diseases, it can increase the occurrence of others. Tomato leaf mold disease is one that’s showing a significant increase. It’s caused by a fungus formerly known as Cladosporium fulvum, but now known as Fulvia fulva by producers and those in the seed trade, and Passalora fulva by mycologists. The disease is rarely seen on field-grown plants, and when it’s observed in the field, it’s due to infected greenhouse-grown transplants.

C. Spider Mites Two-Spotted Spider Mite

The two-spotted spider mite is the most common mite species that attacks vegetable and fruit crops in New England. Spider mites can occur in tomato, eggplant, potato, vine crops such as melons, cucumbers, and other crops. Two-spotted spider mites are one of the most important pests of eggplant.

D. Target Spot

Target spot on leaf is difficult to recognize in the early stages, as the disease resembles several other fungal diseases of leaf. However, as diseased plants ripen and turn from green to red, the fruit displays circular spots with concentric, target-like rings and velvety black, fungal lesions in the center. The “targets” become pitted and larger as the matures.

E. Yellow Leaf Curl Virus

Yellow leaf curl virus (TYLCV) is a DNA virus from the genus Begomovirus and the family Geminiviridae. TYLCV causes the most destructive disease of plant leaf, and it can be found in tropical and subtropical regions causing severe economic losses.

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F. Leaf Mosaic Virus

Mosaic virus symptoms can be found at any stage of growth and all parts of the plant may be infected. They are often seen as a general mottling or mosaic appearance on foliage. When the plant is severely affected, leaves may look akin to ferns with raised dark green regions. Leaves may also become stunted.

G. Leaf Spot on Septoria

One of the most prevalent crop plant leaf diseases is the septoria leaf spot. A tiny, round patch with a greyish-white center and black borders is the first sign of this fungus' presence. In the center, tiny black specks may appear. The leaves of sensitive crop plants become yellow, wither, and fall off due to prolonged exposure to hot, humid conditions.

H. Early Blight (Alternaria)

Alternaria is a parasite that causes crop leaf spots and an early curse. On the lower leaves, brown or dark regions with dim edges arise, practically like an objective. Organic product stem closes are exceptionally touchy, creating tremendous, profound dark blotches with concentric rings. A fungus causes this crop plant disease, which appears after the plants have produced fruit.

I. Blight in the Late Stages

Late blight, a plant disease caused by the fungus Phytophthora infestans, arises in perfect, wet conditions after the growth season. Frost damage with uneven green-black splotches emerges on plants. Fruits with large, irregularly shaped black areas can quickly be destroyed. This fungus, which causes plant disease, also affects and can be transmitted through them. The same precautions should be used as with septoria leaf spot.

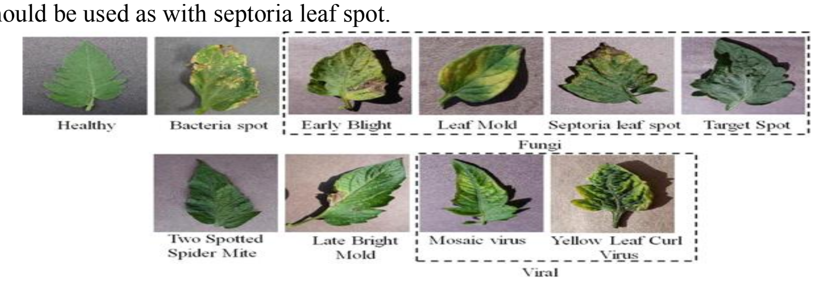

Figure 2: Tomato Healthy and Types of Disease

J. Early Blight (Alternaria)

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II. EXPERIMENT

2.1 Data Description

We use the Kaggle dataset as the basis for the evaluation of the leaf health recognition task [8]. The dataset is divided into two parts: 87867 total images in the dataset, Total testing & Total training images: Data is split in 80/20 ratio, i.e. 80% or training and 20% testing symptoms can be found at any stage of growth and all parts of the plant may be infected. They are often seen as a general mottling or mosaic appearance on foliage. When the plant is severely affected, leaves may look akin to ferns with raised dark green regions. Leaves may also become stunted .testing samples are used for training the deep

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neural network. The dataset allows machine learning researchers with fresh ideas to go right into a critical technological area without gathering or generating new data sets, allowing for a direct comparison to the efficacy of earlier work. The data collection is created using the Leaf picture, which includes healthy and unhealthy individuals of various classes [7]. The data set is split into two sections: one huge group is utilized for training the deep neural network, and another sample is used to validate the model. Finally, a set known as the test set is employed. All models and training are done with the Keras with TensorFlow as a deep learning library using high-end GPUs such as T4 and P100 and TPUs. The Adam optimizer was used for all architectures, and the loss function was the categorical cross-entropy function. We also used ReLU activation functions for all layers, except the last dense layer [8].

2.2 Proposed Methodology

A. Problem statement

In terms of agriculture preservation, our farmers have to check the leaves and illness of the plants by getting the sample itself or checking on the field. There might be a shot at blunder because of the absence of information and numerous different variables. So we need to automate this with the goal that farmers can rapidly build their creation.

B. Methodology

Deep learning increased the learning capacity of the features directly in highly dimensional unprocessed s data, the deep learning algorithms in images and extraction of specific audio segments, and supervised learning in general. Hence, as a strong candidate for classification task modulation, an integrated understanding of deep Learning algorithms solves the central problem as the characteristics of the samples are selected and extracted [5]. Therefore, it shows the combination of simple functions in more efficient and more complex features to achieve the classification more efficiently and complicated. Moreover, deep neural networks have a multilayer structure that can better extract the signal properties by avoiding the lengthy manual selection of data properties. In this project, we create a small-scale deep convolutional neural network (DCNN), assess its performance, and then develop a more advanced deep learning network based on various art data and techniques [7].

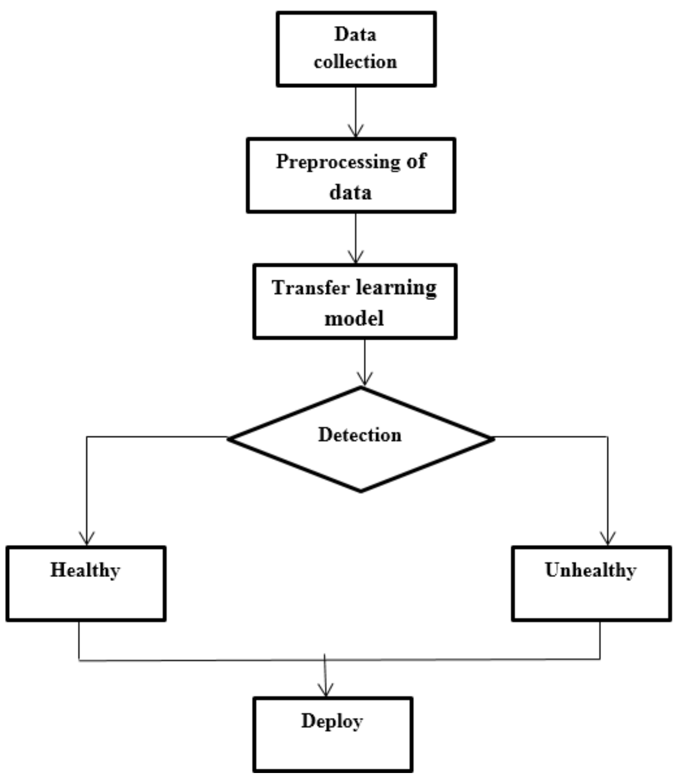

Figure 3: Proposed Methodology of the system

C. The Architecture of DCNN is as follows

We developed "IDENTIFICATION of leaf disease using transfer learning" using Deep learning. We just took a step and started to collect lots of images of crop leaves. We require space capability to get the correct information. Then, at that point, we pick which calculation is ideal for tackling this issue, and we choose "Convolution Neural Network" not surprisingly (CNN). Be that as it may, we gain less precision utilizing move learning engineering, which admirably prepares and tests datasets.

Pre-processing & feature extraction, we select leaf data such as color, shape, and texture is helpful in pattern recognition, classification. It gives us more than 81% accuracy on training and validation data set in just 20 epochs. After that, we deployed this mod model on the flask [6].

D. Evaluation Method

In This project, we have built a DCNN from scratch:

- Dividing the dataset into two parts, i.e., training dataset (70295 leaf image) and validation dataset (17572 leaf image).
- Our DCNN model contains one input layer, multiple conv2D layers, 2 Dense layers and one output layer with a few dropout layers in between.
- On the training and Validation dataset, the DCNN model is trained.
- After training, true-positive, false-positive, accurate- negative, false-negative of the test set were recorded successively.

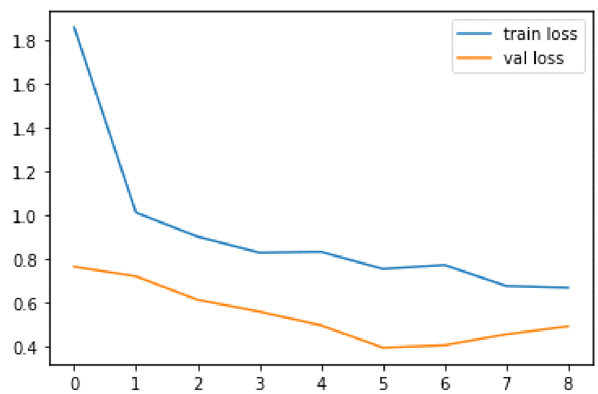

Figure 3: Training vs. validation loss of cnn model.

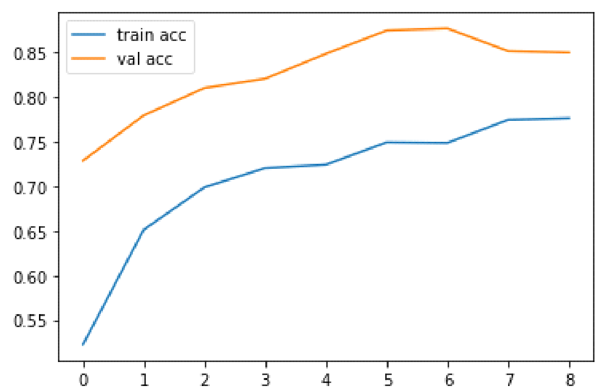

Figure 4. Training vs validation loss of cnn model.

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III. Result Analysis and Discussion

Our task was to train a deep convolutional neural network (CNN) to identify and classify leaf images. We used the Plant Leaf Disease Dataset from Kaggle, which we have selected in two categories [Diseased Leaf, Fresh Leaf], a dataset containing leaf images in the form of arrays from these two categories. Each category's leaf comes in a variety of leaf photos from various perspectives [8].

DL techniques continue to show great potential in increasing identification sensitivity and accuracy, particularly for short-term data. DCNN, on the other hand, can extract features automatically, saving time and effort. The findings are reported once the model has been evaluated on the test dataset. The model's overall accuracy is 81%. When we build a model first time, the model tries to fit all the data that is why it has very low accuracy, so we reassign all the weighted data to your model so the model can run and reassign error then call the epoch of the model which is continuously running with data and try to increase accuracy and decrease the loss of the data [5]. The accuracy result of our deep learning model clearly shows that when we grow the model epoch, there is an increment inaccuracy. The accuracy result of our deep learning model clearly shows that when we increase the model epoch, there is an increment in accuracy. The model loss result clearly shows that when we increase the model epoch, loss decreases.

IV. Conclusion

In this work the plant disease classification done through our system by deploying our model on a flask that observes illness and infected leaves. The proposed work has several verticals in leaf detection. Up to now, we have investigated various diseases in plant leaf. In future, we will segregate the illness whether or not it is laid down with low microorganisms, fungi or infectious agents and specify the answer to the farmer within the field.

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