

# Digital image processing technique for detection and classification of different diseased plant

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**Abstract:** Plant quality and productivity are significantly impacted by plant diseases. Plant disease detection can be done via digital image processing. In the field of digital image processing, deep learning has recently done significantly better than conventional methods. Experts are now particularly interested in the study area of deep learning-based plant disease diagnosis. Plant diseases and pest detection issues are defined in this study, and the effectiveness of the methods is contrasted with conventional ones. This article reviews the current literature on classification networks, detection networks, and segmentation networks for deep learning-based plant disease and pest detection. The advantages and disadvantages of each strategy are examined in light of the variations in network structure. We compare the effectiveness of earlier studies using common datasets. This study investigates potential challenges associated with deep learning-based plant disease and pest identification in practical contexts. Along with potential research directions and resolutions to the problems, a number of recommendations are also provided. Finally, this paper analyses and predicts the potential future directions for deep learning-based plant disease and pest detection.

## I. INTRODUCTION

Identifying plant diseases and pests is one of the key research areas in the field of machine vision. It is a technique that examines photos of plants to see if they are afflicted with pests and diseases using machine vision equipment. Machine vision-based technologies have largely taken the place of traditional naked-eye diagnosis of plant diseases and pests in agriculture today.

Common image processing techniques or manually created features and classifiers are frequently used in machine vision-based systems for detecting plant diseases and pests. The many characteristics of plant diseases and pests are frequently used in this type of technology to create the imaging scheme and select the right light source and shooting angle. This makes it easier to achieve consistent lighting in pictures. Although With thoroughly thought-out imaging techniques, the difficulty of building a standard algorithm can be significantly decreased, but the cost of the application will rise. It's frequently difficult to presume that outdated methods designed to totally avoid the effects of scene changes on recognition outcomes will work in real-world situations.

### Background Work:

The problem statement notes a number of challenges, although research on plant disease detection is still ongoing. Many other tactics have been proposed over the years. In conventional systems, support vector machine algorithms can be utilized to recognize and classify different plant diseases. Depending on the type and stage of the disease, this method's classification accuracy for diagnosing sugar beet diseases ranged from 65% to 90%. For the autonomous identification and categorization of plant diseases, K-means was used as a clustering algorithm alongside another approach based on leaf images and using ANNs. The ANN contained 10 hidden layers.

## II. LITERATURE SURVEY

India has seen a huge revolution in agri-tech. On their fields, the majority of farmers do not use cutting-edge technology. We constantly see stories regarding IoT-related agriculture in various periodicals, but none of them are well applied in Indian farms. There is a significant gap between farmers and technology in India. Many start-ups have sprung up in an effort to bridge the gap between farmers and technology. Even numerous multinational corporations are now investing in India's agri-tech sector. Food demand is increasing exponentially as a result of population growth. Farmers are using

technologies like temperature and moisture sensors, drones, smart irrigation, terrain contour mapping, self-driving and GPS connected tractors/rovers to produce food more sustainably.

Modern agriculture has a number of challenges. Farmers and other agricultural actors must now consider regional climatic and geographic factors as well as global ecological and political challenges in order to assure their financial survival and the sustainability of their businesses.

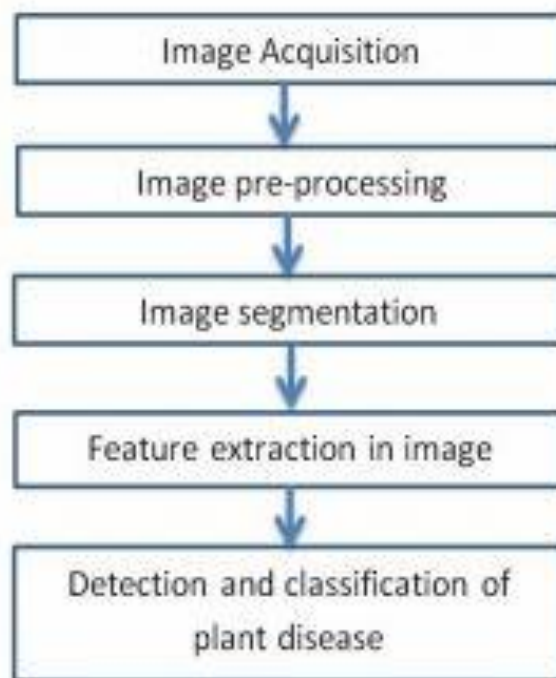
To support a growing world population, food production must continually increase, but arable land is still a limited resource. New bioenergy requirements or changing food tastes put increasing pressure on agriculture productivity, while settlement and transportation continue to consume more and more land. Traditional agricultural regions are under danger, and new dangers and uncertainties are brought about by expected and visible changes in the global climate, shifting patterns of precipitation, and global warming.

The automation technology is the main area of focus for Indian start-ups. Automated drones and bots are utilised in farms to tend to the produce and keep an eye on it. Similarly, the technology used is evolving daily from normal farm pesticide and fertiliser spraying to precision target spraying. Artificial intelligence, machine learning, and deep learning algorithms are used to watch the crops carefully, identify problematic agricultural regions, and then apply a fix there.

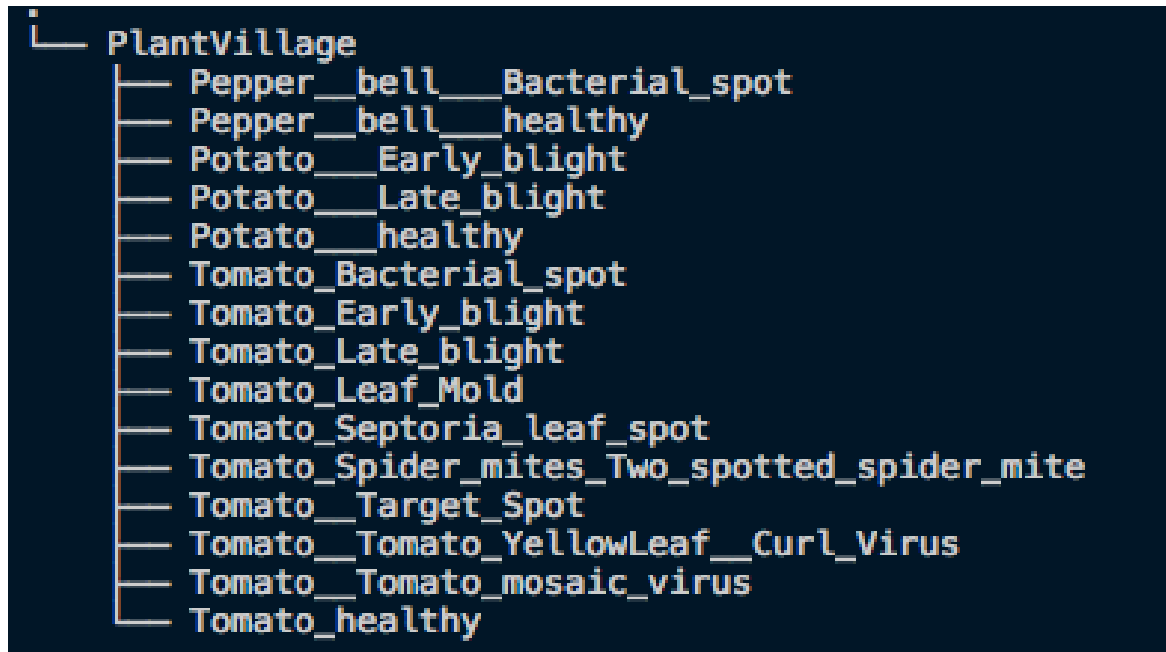
Numerous start-up businesses in India have launched their automated agricultural technology products. To increase crop yield, most drones and digital apps are used. The field is sprayed with radar by drones that have been deployed. The entire farm's latitude and longitude are marked on the map, and radar is utilized to keep the drone and farm at a constant height to prevent any form of collision. This system can quickly and widely distribute insecticides and fertilizers across vast farms. Both the farmer's time and the crop are saved by doing this.

### III. METHODOLOGY

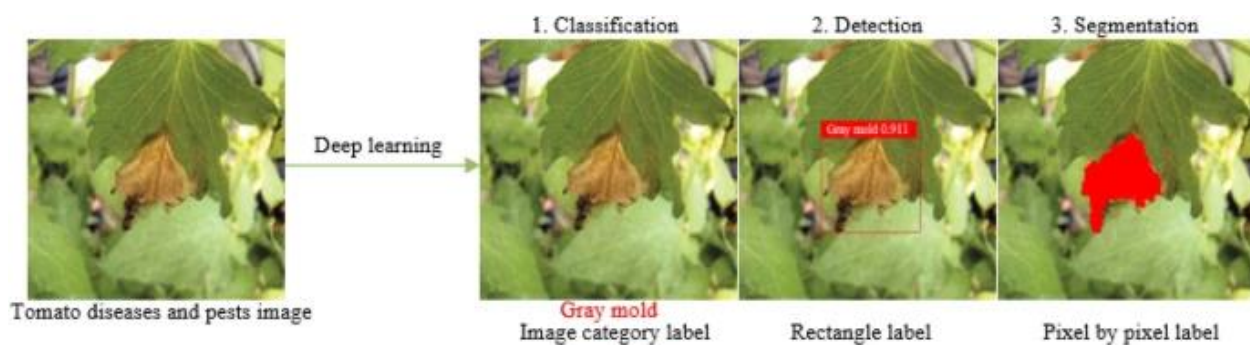
In this section, the basic steps for plant disease detection and classification using image processing are shown



On the majority of typical machines, it is challenging to train the classification model locally due to the restricted processing capability. As a result, we utilize Google Colab notebook's processing capability while it rapidly and easily connects us to a free TPU instance.

**Definition of plant diseases and pests detection:**

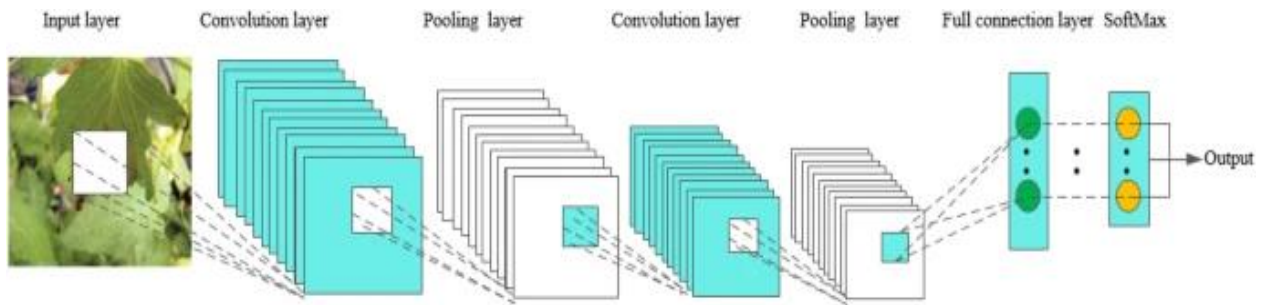
In contrast to the precise classification, detection, and segmentation problems in computer vision, the requirements of plant disease and pest identification are quite generic. Actually, the specifications can be divided into three groups: what, where, and how. The computer vision classification problem is equivalent to "what" in the first phase. As seen in Figure, the name of the category to which it belongs is given. The classification work done at this stage just gives the image's category information. The second stage's "where" alludes to the location problem in computer vision, and this stage's placement corresponds exactly to the sensation of detection. a range of details, like the length and area.



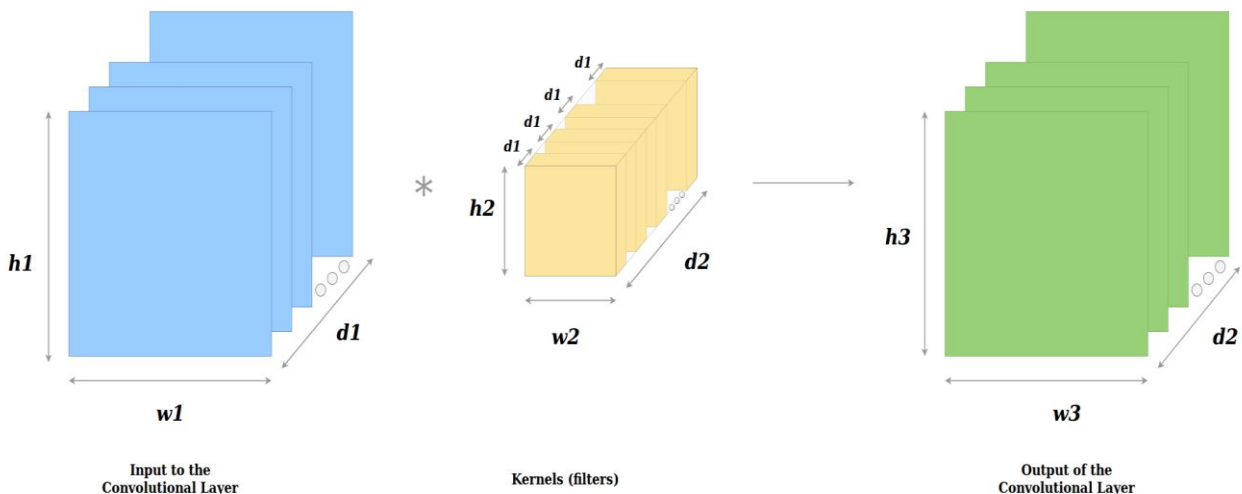
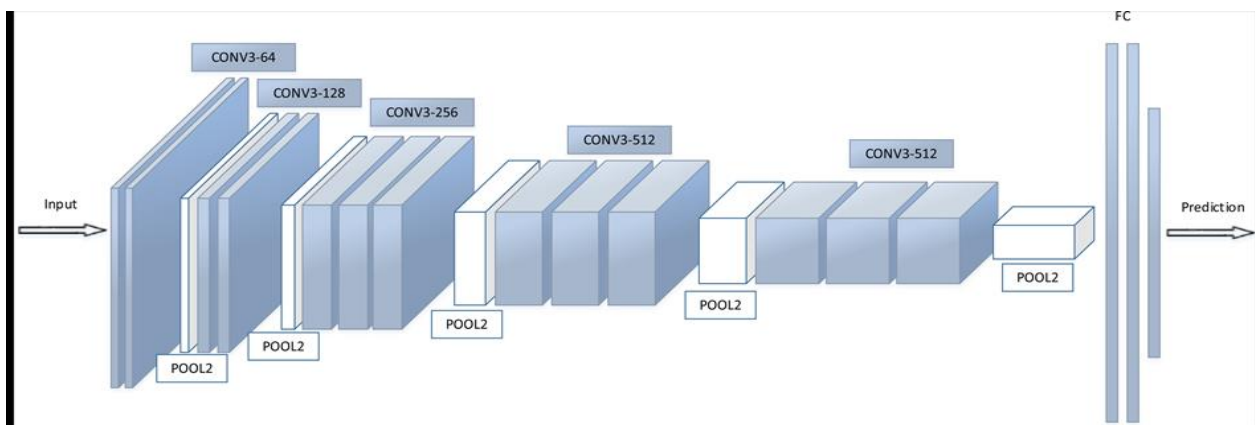
Despite having distinct function needs and targets, the three phases associated with plant disease and pest detection are essentially interchangeable and mutually inclusive. The "where" in the second stage, for instance, combines the "what" in the first stage's method, and the "how" in the third stage can finish the "where" in the second stage's assignment. The "what" in the first stage can also achieve the goal of the second and third phases by employing a variety of ways. Therefore, in the present inquiry, the term a "issue" will only be distinguished when various network topologies and functionalities are used. Thus, the issue in this study will be referred to as "plant diseases and pests detection" throughout the remainder of the article.

**Convolutional neural network:**

We shall examine what convolutional neural networks—abbreviated ConvNets—are. ConvNets are the supercomputers that advanced deep learning's use of images. The input for ConvNets is an image, or more precisely, a 3D Matrix. CNNs, or convolutional neural networks, are able to perform convolutional operations and have a complex network structure. The convolutional neural network model is represented by the input layer, convolution layer, pooling layer, full connection layer, and output layer in Fig. 2. In one scenario, the neurons from the convolution layer and the neurons from the pooling layer are connected, but there is no need for a complete connection between them. One popular deep learning model is CNN.



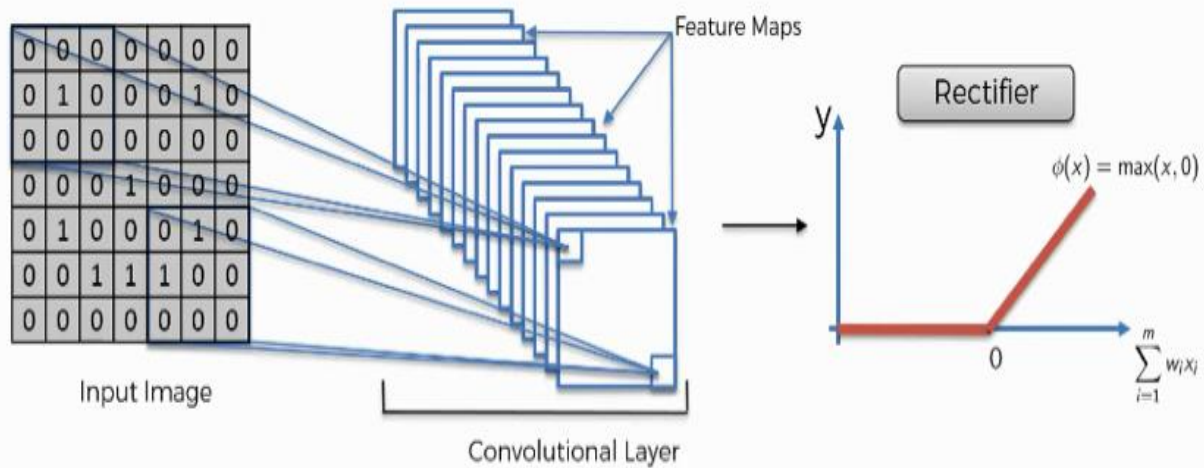
The convolution layer is where a convolution core is first defined. The local receptive field, often known as the convolution core, is the main advantage of the convolution neural network. During data processing, the convolution core moves through the feature map to extract some feature data.



### ReLU layer:

The ReLU (rectified linear unit) layer comes next after our convolution layer. To make the network more nonlinear, you incorporate an activation function into your feature maps. Due to how highly non-linear images are, this occurs.

It removes negative values from an activation map by setting them to zero. Convolution is a linear operation that comprises matrix multiplication and element-wise addition. We want CNN to learn from non-linear data from the actual world.



Using the rectifier function will increase the nonlinearity of our images. Given that photographs are intrinsically non-linear, we wish to achieve that. Any image you view has a lot of non-linear components, including the borders, colours, and pixel transitions.

The rectifier works to further break up the linearity in order to make up for whatever linearity we may introduce into an image while using the convolution technique. To further understand how that truly functions, we may examine the following image and see the changes that occur during the convolution and rectification processes.

#### IV. CONCLUSION

As a result, we have finished extracting features, training data, and classifying images. the Image Processing Toolbox, and the Statistics and Machine Learning Toolbox. Currently, the outputs consist of training data in the form of image categories, K-Means clustering for image classification, moisture content, and withstanding prediction.

The method is finished using training data and picture dataset categorization. For detection and prediction analysis, the trained data are compared to the test input image. For perfect precision, we are employing unsupervised learning. Let's use trained data for Indian rice plants as an example and test input for African rice plants. The little change in appearance would result in poor accuracy. We are concentrating on unsupervised learning as a result.

The Fuzzy C-Means method would provide 99% accuracy in the scenario. Even though the name implies that the data may be fuzzy, we will nonetheless receive accurate precision. As a result, we are staying away from supervised learning strategies.

The overall system results show that the Mobile Net model outperforms the competition and delivers more precise sickness detection. More plant species and their diseases will be included in the experiment. The model will also be improved further by raising the test and training parameter values. Before they further damage fields, plant diseases are severe food dangers that need to be controlled.

#### V. RESULT

Using matplotlib, we plotted a graph for Training and Validation accuracy and Training and Validation loss.

```
In [15]:  
acc = history.history['acc']  
val_acc = history.history['val_acc']  
loss = history.history['loss']  
val_loss = history.history['val_loss']  
epochs = range(1, len(acc) + 1)  
#Train and validation accuracy  
plt.plot(epochs, acc, 'b', label='Training accuracy')  
plt.plot(epochs, val_acc, 'r', label='Validation accuracy')  
plt.title('Training and Validation accuracy')  
plt.legend()  
  
plt.figure()  
#Train and validation loss  
plt.plot(epochs, loss, 'b', label='Training loss')  
plt.plot(epochs, val_loss, 'r', label='Validation loss')  
plt.title('Training and Validation loss')  
plt.legend()  
plt.show()
```

Fig. Visualization of Training Output.

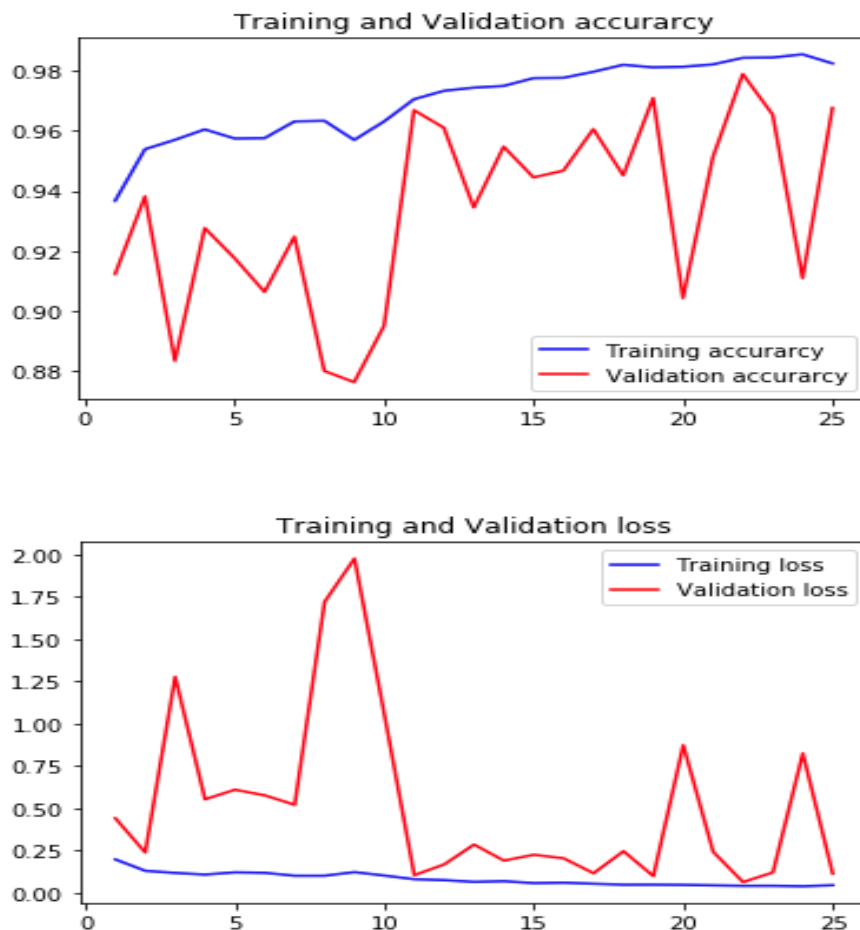


Fig. Visual Output of Models

**Model Overall Result:**

As you can see in the screenshot below, django and flask were used to develop our website. We only need to upload an image to the webpage, and the outcome will be displayed below the image.



**Fig. Uploaded Image of Potato.**

Plant Disease Diagnosis

Plant Disease Diagnosis

Browse... 0d9dbf50-53a9-42b2-8b29-0360fb7dbd98\_\_RS\_Early.B 6692.JPG



Result: Potato\_\_Early\_blight

Fig .webpage snapshot after the prediction of results.

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