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# Plant Leaf Disease Detection using Convolutional Neural Networks

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**Abstract:** Agriculture is back bone of economy for most of the countries. In India, 50% of our population is dependent on agriculture field. According to NITI Aayog CEO Amitabh Kant, India cannot achieve 9-10 % GDP growth without revolution in the farm sector for next 30 years. Agriculture sector is seeking innovation for improving crop yielding because of unpredictable climatic changes, the rapid increase in population growth and food security concerns. And specially in the pandemic situations there is need of quality of food for perfect nutrition. As to reach the increasing demand for quality and quantity of food, there is need of Artificial intelligence-based technology in agriculture. So, in order to increase production with quality we need to adapt to AI based application such as precision farming, disease detection, smart sprayers with help of deep learning algorithms, image processing, artificial neural network (ANN), convolutional neural network (CNN), sensors, wireless communication systems. With help of technology we can effectively use chemicals and reduce expenditure. As a result of this, we will be able to achieve the best quality and increase in productivity.

**Keywords:** Artificial Intelligence, deep learning, image processing, artificial neural network, convolutional neural network.

## I. INTRODUCTION

The agriculture sector continues to be crucial to the sustainable growth and development of the Indian economy. It contributes significantly to production, employment and demand generation through various backward and forward linkages of 1.3 billion people of India. Moreover, the role of the agricultural sector in reduce poverty and ensuring the sustainable development of the economy is well established. Modern high input mono cropping based intensive agriculture has resulted in loss of biodiversity, outbreaks of pest and disease, degradation of soil and water. The crop yield losses, on field and during harvest period, caused by pests, diseases (Kumar et. al).

Agriculture is the oldest and most important professions in the world. Pest management one of the most important part while cultivating crops. The traditional techniques of uniform spraying pesticides and chemicals is used widely, but such conventional spraying techniques leads to excessive, injudicious, and less effective utilization of applied chemicals. The uniform spraying techniques results in wastage of applied chemicals. In India, Farmers blindly use such techniques without insuring its effectiveness which can adversely effect on soil fertility rate. Many of the time crops gets affected by external factors. There are many factors that leads to development of pathogens, diseases such as climate change, access amount of water, etc. So, to reduce the cost of chemicals and increase its precise use for better crop yield, we need some AI based techniques. Artificial intelligence enables farmers to use modern techniques that will help to save time as well as cost.

Artificial intelligence is an emerging technology in the field of agriculture. The technology has enhanced crop production and improved real-time monitoring. Artificial intelligence-based equipment has help farmers to access improvised techniques to enhanced the production. It is crucial to prevent waste of financial and other resources and simultaneously keep crops in healthy condition. Artificial intelligence helps to use pesticide according to severity of crop by using various deep learning algorithms. Detection of disease severity will help to treat the crop in right manner, and also it is important to diagnose the spread of disease and pest in early stage. So, it is important to limit the spread of disease and pest to minimize the financial loss. Machine learning techniques help to detect the severity of crop by image processing which will help farmers and save their time. AI also able to give right treatment procedure. Some disease is not easily get detected by experienced person because there is possibility that crop may get affected by two or more disease simultaneously.

Tomato crop is one of the common vegetables in India. Tomato crop cultivation area in India spans around 3,50,000 hectares approximately and the production quantities roughly sum up to 53,00,000 tons, making India the third largest tomato producer in the world (Tyagi, 2017). The methodology suggested in the paper contains most common tomato leaf diseases such as Bacterial spot, Early blight, Late blight, Leaf Mold, Septoria leaf spot, spider mites, Target spot, mosaic virus, Yellow Leaf Curl virus. The proposed methodology consists of three major steps: data acquisition, pre-processing and classification. the image dataset used for implementing purposed methodology were acquired from publicly available dataset. In purposed methodology two deep learning convolutional neural network (CNN) models are implemented on same dataset.

## II. OBJECTIVES

- A. To predict crop disease and its severity to help farmers in accurately use the pesticides.
- B. To understand different algorithms and its accuracy to predict common diseases.

Following hypotheses are proposed to attain the above objectives using experiments: -

- 1) *H1*: "To detect plant disease with AI technology, VGG is the best architecture because it has high accuracy over the remainder."

## III. LITERATURE REVIEW

It is important to have knowledge about the previous research in same field. Plant disease detection is one of the major research areas in image processing and deep learning. As plant disease detection is widely used to get accurate classification. In this paper, we discuss some of the techniques that were implemented in the relevant field. The authors paper [1] proposed, a brief idea of various AI applications in agriculture in respect to diseases and pest Management. And what are different technique that can be apply with their strength and limitation. In paper [8] with help of RGB kernel based SVM and PCM analysis researcher reach a accuracy of above 95% in rice crop but there were still some factors such as noise which affect while artificial simulation. The research paper [8] proposed a technology which is used to detect the chemical residues on apple in postharvest stage. In this technology researchers used Otsu segmentation algorithm with the use of CNN network. The average recognition rate was obtained in between 95-96% in single band images and in true positioned based images it was 99.09%. The research paper portrayed the effectiveness of CNN network over KNN and SVM methods. However, when two hyperspectral images are in the same band and have a similar appearance, the network is prone to detection errors. Researchers were trying to solve that by increasing parameters of convolution kernel. The authors of paper [9] proposed a research included 5 different type of wheat; experimental classification model consists of five separate VGG-16 CNN models, considering one for each of the paddy crop varieties. The maximum average stress classification accuracy of 95.08% was achieved. In Paper [12] implementation of Five CNN architectures was used for detection of disease. Researcher used 3 approach for training and testing pattern in which (VGG and Alex Net) architecture showed promising results, The Research paper portrayed effectiveness of two architecture over other three, in which VGG shows accuracy of 99%. The research paper [13] proposed Particle swarm optimization algorithm for image segmentation. The research effectively shown the efficiency of proposed algorithm in recognition and classification sunflower leaf diseases with an effective accuracy of 98%. Researchers were looking forward to implement ANN, hybrid algorithms for faster and effective recognition rate. In research paper [14], a tomato leaf diseases detection and classification method were presented based on Convolutional Neural Network with Learning Vector Quantization algorithm. A confusion matrix was created having 20 images for each class of disease.

The authors of paper [17] proposed different machine learning architecture for detection of banana plant disease. Architecture involves RESNET50, INCEPTIONV2, MobileNetV1 models. For training researcher use COCO database with simple random sampling technique. The Research portrayed the effective architecture that was used by researchers out of which RESNET50 showed effective results while detecting whole plant and with INCEPTIONV2 showed better results in fruity and flower plants.

## IV. PROPOSED METHDOLOGY

The proposed approach includes the three important stages: Data Acquisition, Data pre-processing and Classification. For the proposed methodology transfer learning method is used.

### A. Data Acquisition

The tomato leaf disease images have been taken from open source internet repository. The acquired dataset consists of around 22930 images belonging to 10 different classes. The dataset includes images of all major kinds of leaf diseases that could affect the tomato crop. Each of the downloaded images belongs to the RGB color space by default and were stored in the uncompressed JPG format.

Images were classified into two categorize train and test images.

### B. Data Pre-processing

The images acquired are of minimum noise and hence no step involve of noise minimization. The images are then resized to 224\*224 resolution in order to speed up the training process and make the model training computationally feasible. The input and target variables are standardized to speed up the training process. It is also need to ensure that initialized and terminated values involved are appropriate. for this, we normalize the images to get all the pixel values in the same range.

### C. CNN Model Configuration and Architecture

The proposed work has employed the pre-trained VGG-16 and VGG-19 CNN model for the classification of healthy and infected leaf. The schematic structure of the network VGG-16 model layers are shown in Fig. 1. The model is a homogeneous architecture that only performs  $3 \times 3$  convolutions and  $2 \times 2$  pooling from the beginning to the end. The model is implemented using a higher-level Python library Keras which runs over an open source deep learning framework TensorFlow as a backend. The image dimension is set to  $224 \times 224$  pixels with depth 3 (RGB channels) and the images are passed through the stack of convolutional layers with the convolution filter size  $3 \times 3$  and convolution strides in x and y directions (1,1) pixels. 'SoftMax' function is applied to the final layer to ensure the predicted probability output values are in the range of 0 and 1. The network uses 15 epochs and a batch size of 32. The network has been optimized using the Adam optimization algorithm with categorical cross entropy logarithmic loss function.

Model: "functional\_1"

| Layer (type)                     | Output Shape          | Param # |
|----------------------------------|-----------------------|---------|
| input_1 (InputLayer)             | [(None, 224, 224, 3)] | 0       |
| block1_conv1 (Conv2D)            | (None, 224, 224, 64)  | 1792    |
| block1_conv2 (Conv2D)            | (None, 224, 224, 64)  | 36928   |
| block1_pool (MaxPooling2D)       | (None, 112, 112, 64)  | 0       |
| block2_conv1 (Conv2D)            | (None, 112, 112, 128) | 73856   |
| block2_conv2 (Conv2D)            | (None, 112, 112, 128) | 147584  |
| block2_pool (MaxPooling2D)       | (None, 56, 56, 128)   | 0       |
| block3_conv1 (Conv2D)            | (None, 56, 56, 256)   | 295168  |
| block3_conv2 (Conv2D)            | (None, 56, 56, 256)   | 590080  |
| block3_conv3 (Conv2D)            | (None, 56, 56, 256)   | 590080  |
| block3_pool (MaxPooling2D)       | (None, 28, 28, 256)   | 0       |
| block4_conv1 (Conv2D)            | (None, 28, 28, 512)   | 1180160 |
| block4_conv2 (Conv2D)            | (None, 28, 28, 512)   | 2359808 |
| block4_conv3 (Conv2D)            | (None, 28, 28, 512)   | 2359808 |
| block4_pool (MaxPooling2D)       | (None, 14, 14, 512)   | 0       |
| block5_conv1 (Conv2D)            | (None, 14, 14, 512)   | 2359808 |
| block5_conv2 (Conv2D)            | (None, 14, 14, 512)   | 2359808 |
| block5_conv3 (Conv2D)            | (None, 14, 14, 512)   | 2359808 |
| block5_pool (MaxPooling2D)       | (None, 7, 7, 512)     | 0       |
| flatten (Flatten)                | (None, 25088)         | 0       |
| dense (Dense)                    | (None, 10)            | 250890  |
| Total params: 14,965,578         |                       |         |
| Trainable params: 250,890        |                       |         |
| Non-trainable params: 14,714,688 |                       |         |

Fig1. Schematic structure of the VGG-16 CNN model layers.

The schematic structure of the network VGG-19 model layers is shown in Fig. 2.

| Model: "functional_1"            |                       |         |
|----------------------------------|-----------------------|---------|
| Layer (type)                     | Output Shape          | Param # |
| input_1 (InputLayer)             | [(None, 224, 224, 3)] | 0       |
| block1_conv1 (Conv2D)            | (None, 224, 224, 64)  | 1792    |
| block1_conv2 (Conv2D)            | (None, 224, 224, 64)  | 36928   |
| block1_pool (MaxPooling2D)       | (None, 112, 112, 64)  | 0       |
| block2_conv1 (Conv2D)            | (None, 112, 112, 128) | 73856   |
| block2_conv2 (Conv2D)            | (None, 112, 112, 128) | 147584  |
| block2_pool (MaxPooling2D)       | (None, 56, 56, 128)   | 0       |
| block3_conv1 (Conv2D)            | (None, 56, 56, 256)   | 295168  |
| block3_conv2 (Conv2D)            | (None, 56, 56, 256)   | 590080  |
| block3_conv3 (Conv2D)            | (None, 56, 56, 256)   | 590080  |
| block3_conv4 (Conv2D)            | (None, 56, 56, 256)   | 590080  |
| block3_pool (MaxPooling2D)       | (None, 28, 28, 256)   | 0       |
| block4_conv1 (Conv2D)            | (None, 28, 28, 512)   | 1180160 |
| block4_conv2 (Conv2D)            | (None, 28, 28, 512)   | 2359808 |
| block4_conv3 (Conv2D)            | (None, 28, 28, 512)   | 2359808 |
| block4_conv4 (Conv2D)            | (None, 28, 28, 512)   | 2359808 |
| block4_pool (MaxPooling2D)       | (None, 14, 14, 512)   | 0       |
| block5_conv1 (Conv2D)            | (None, 14, 14, 512)   | 2359808 |
| block5_conv2 (Conv2D)            | (None, 14, 14, 512)   | 2359808 |
| block5_conv3 (Conv2D)            | (None, 14, 14, 512)   | 2359808 |
| block5_conv4 (Conv2D)            | (None, 14, 14, 512)   | 2359808 |
| block5_pool (MaxPooling2D)       | (None, 7, 7, 512)     | 0       |
| flatten (Flatten)                | (None, 25088)         | 0       |
| dense (Dense)                    | (None, 10)            | 250890  |
| Total params: 20,275,274         |                       |         |
| Trainable params: 250,890        |                       |         |
| Non-trainable params: 20,024,384 |                       |         |

Fig 2. Schematic structure of the VGG-19 CNN model layers.

The network uses 15 epochs and a batch size of 32. The network has been optimized using the RMSprop with learning rate 0.001 optimization algorithm and 'SoftMax' activation function is applied to last layer with categorical cross entropy logarithmic loss function.

## V. EXPERIMENTAL RESULTS AND DISCUSSION

For two VGG models various image augmentation techniques such as rescale, shear range, zoom range, horizontal flip is use. With VGG-16 model a 95% trained accuracy and 91.9% validation accuracy is achieved. In VGG-19 model, 90.8% trained accuracy with 86.25% validation accuracy is achieve. Two models accurately predict the disease of the crop.

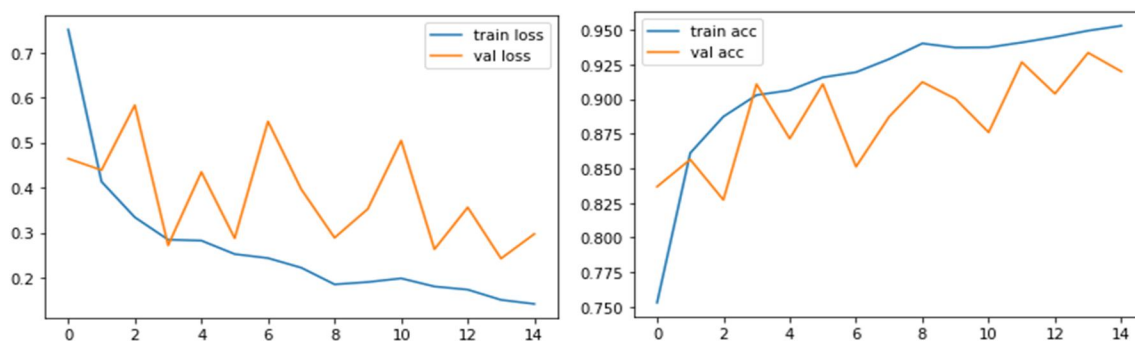


Fig 3. Plot of accuracy and loss against epoch (VGG16)

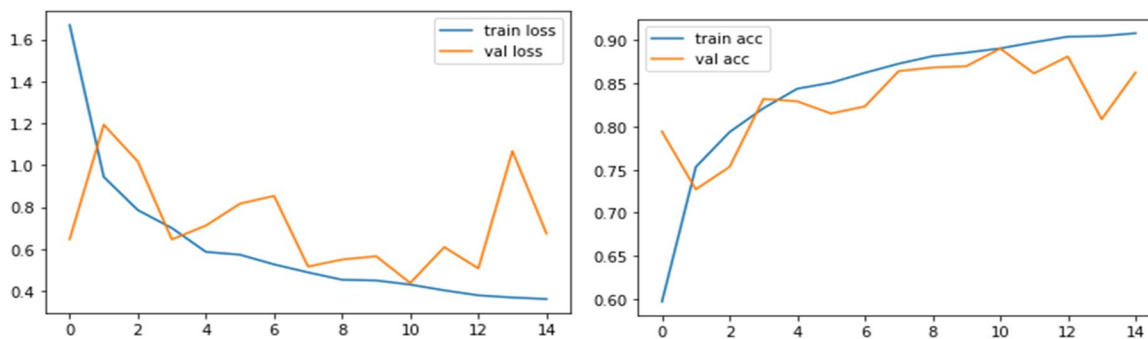


Fig 4. Plot of accuracy and loss against epoch (VGG19)

## VI. CONCLUSION AND FUTURE SCOPE

In the present work, an attempt has been made to automate the recognition and classification of tomato leaf using deep learning technique. 10 different tomato disease varieties are present in dataset. The best performing pre-trained deep learning model VGG-16 and VGG-19 has been used in the classification task. Different learning rates and optimizers could also be used for experimenting with the proposed model as a part of the future work. It could also include new architecture to improve the accuracy and prediction of disease. A common application could be made in future to distinguish different type of crop disease to help farmers in agriculture.

## VII. ACKNOWLEDGEMENT

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