IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

TOMATO CROP DISEASE DETECTION USING MOBILENET

[1]Hrishikesh Deokar, [2]Karan Devkate, [3]Sahil Gadge, [4]Pratik Kamble, [5]Dr. Shabnam Sayyad

[1]Student, [2]Student, [3]Student, [4]Student, [5]Associate Professor

[1]Computer Engineering,

[1]AISSMS COE, Pune, India

Abstract: Agriculture is the practice of farming, which includes the preparation of the land for the growth of plants, the care of animals, and the production of other goods like oil, wool, and other goods. Diseases in crops adversely affect the income of farmer gained from agriculture. The nation's economy is impacted as a result of this. This makes it necessary and important to detect and solve these problems. But this need to be done as early as possible which cannot be done by traditional methods. Thus, we proposed a model which makes use of deep learning to identify the diseases in tomato crop. This will prove helpful for the farmers for detection of disease and finding appropriate remedy.

Index Terms **- Agriculture, Deep Learning, Convolutional Neural Networks, Disease detection, MobileNet, Pesticide, Image classification.**

I. Introduction

Agriculture is the main food source across the world. Due to the rapidly growing population, agriculture also needs to be efficient in order to fulfil the demand of this population. Agriculture productivity is declining due to factors like climate change, global warming, crop diseases, decrease in pollinators, lack of efficient irrigation, etc. Crop Disease reduces the food quality and also the production. Crop diseases not only badly affect the small-scale farmers (whose primary income source depends on efficient cultivation), but also affects the food safety at the global level. The sooner we can identify the disease on the crop, that much we can benefit to control the disease. Due to the rise in new technologies like computer science it has been possible to get an efficient solution to this problem.

The objective of our paper is to develop a deep learning model to detect and classify diseases in tomato crops. This is done by using leaf images. During training we used publicly available dataset containing leaf images of tomato crop.

The Classes in the Dataset can be described as follow:

a. Early blight:

Most common disease affecting tomatoes, caused by the fungi Alternia tomatophila and Alternia solani. Brown spots with the yellow rings are the symptoms of early blight.

figure 1: early blight

b. Late Blight:

Any part of the tomato plant that is above ground can show signs of late blight. Typically, infected leaves contain areas of dead tissue that range in colour from green to brown, encircled by a light green or grey border. Late blight infections can seem water-soaked or dark brown in colour in extremely humid and damp conditions, and they are frequently described as looking greasy.

figure 2: late blight

c. Septoria leaf spot:

The fungus Septoria lycopersici causes Septoria leaf spot. On the undersides of older leaves, symptoms take the form of tiny, water-soaked circular patches about 1/16 to 1/8" in diameter. After that, the centres of these dots change from grey to tan, with a dark-brown border. The spots stand out since they are circular and frequently have a lot of them.

figure 3: septoria leaf spot

d. Bacterial spot:

Bacterial spot affects only green tomatoes not red, caused by Xanthomonas bacteria and its several species. This disease mostly occurs during the rainy season. Damage to plants includes leaf and fruit spotting, causing yield loss, defoliation, and fruit sunburn. Symptoms consist of numerous small, angular, irregular water-soaked spots on leaves and slightly raised, crusted spots on fruit.

figure 4: bacterial spot

e. Leaf Mold:

The fungus Passalora fulva is the source of leaf mould. Only tomatoes grown in greenhouses and high tunnels are often susceptible to tomato leaf mould. High relative humidity (more than 85%) favours the disease. Often, the only area of the plant that is immediately afflicted is the foliage. Infected leaves get withered then die, this indirectly decreases yield. In extreme circumstances, fruit and blooms may also get diseased, directly lowering yield.

figure 5: leaf mold

f. Yellow leaf curl:

Tomato yellow leaf curl is a disease caused due to tomato yellow leaf curl virus. The leaves of infected plants are tiny, curl upward, and exhibit interveinal and marginal yellowing as well as string crumpling. Along with their limited growth, infected plants develop shorter internodes, giving them a bushy appearance. On diseased plants, newly produced flowers frequently do not grow and die off. Fruit output is significantly decreased, especially when plants become infected at a young age.

figure 6: yellow leaf curl

g. Spider Mites:

The two-spotted spider mite is an infrequent pest that can damage vegetable crops during arid weathers. The mites extract the sap from plants, leaving the tops of leaves strained. Leaves of plants infested with mites may turn yellow and dry. The lower surface of affected leaves may appear as light brown or yellow and has a hard texture. Spider mite outbreaks form fine clusters that can cover the entire plant.

figure 7: spider mites

h. Tomato mosaic virus:

The tomato mosaic virus is a plant pathogenic virus that is a member of the tobamoviridae family and genus. Plaques, leaf wrinkling, shrivelling, curling, and uneven fruit ripening are a few symptoms. The tomato mosaic virus can infect any section of the plant and exhibit symptoms at any stage of growth. Yellow mosaic signs on tomato leaves and fruit are a result of the tomato mosaic virus. Tomato mosaic virus symptoms include a frequent patch or mosaic on the leaves. Mosaic leaf spot of several shades of green, which can sometimes disfigure younger leaves.

figure 8: mosaic virus

i. Target Spot:

Corynespora cassiicola is a fungus that causes tomato target spots. The disease begins from the older leaves and goes upwards. The early signs are non-uniform shaped spots (less than 1 mm) with a margin in yellow colour. Target spot infections decrease output both directly and indirectly by decreasing the photosynthetic area and the marketability of the fruit, respectively.

figure 9: target spot

II. Related Work

There are several methods that are deployed for the investigation of agricultural land. Deep Learning has played a very major role in it.

In this Work [1], the model is proposed for classification of plants affected by disease. They developed this model called PDDNN (Plant Disease Detection Neural Network) based on a convolutional neural network (CNN) to focus on plant disease images. They have classified the maize, grape, Tomato, Potato, Apple plants.

In this Work [2], authors have proposed a system for crop disease detection. This described system is based on deep learning and uses CNN to detect disease.

In other work [3], the basics of various plant disease detection techniques were presented. The basics were given in tabular form giving survey of available techniques for solving detection problem.

In this paper [4], authors proposed a system for disease detection in fruit using canny edge detection technique. This System provides a suggestion given by agriculture expert

The paper [5], gives us the brief description about each step required to build the CNN model for plant disease detection. They give information about how to collect images, image pre-processing, augmentation, procedure for training the deep CNN, fine-tunning, etc.

In this paper [6], authors researched different image classification and processing techniques. Also, they used Naïve Bayes and K-Nearest Neighbor algorithms for classification purpose.

In this paper [7], authors have proposed a system that monitors the field and detects the crop diseases periodically. The proposed system uses edge detection and histogram matching for detection and later remedy is suggested to the farmer.

Here [8], we got information about the use of various deep learning algorithms in plant disease detection and also about how different researchers use different deep learning techniques for different plant diseases. The algorithms overviewed in the paper are CNN, GAN and ANN.

Here [9], an improved method of crop disease diagnosis is proposed. This method is based on convolution neural network and deep separable convolution.

In paper [10], they use the CNN model to classify disease from a plant village dataset. This CNN model uses AlexNet architecture to classify disease into 38 classes.

Here [11], for the paddy disease detection they developed a CNN model. Model helps to classify disease into three classes namely Rice Blast, Bacterial Blight and Healthy paddy leaf and provides the solution

In this [12] work, they have compared various approaches of detecting plant disease like CNN, Transfer Learning and Visual Transformers. They have then implemented this detection using Transformers (STN).

III. Methodology

1. Image Acquisition

We used the dataset namely 'Tomato leaf disease detection'.

Table 1 Dataset Information

Dataset Name	**Tomato leaf disease detection**
Dataset Source	Online Website (Kaggle)
Dataset Type	Images
Number of Images	11000
Number of classes	10
Data Format	.jpg

Table 2 Classes Information

Class Name	**Number of Images**
Early Blight	1100
Late Blight	1100
Septoria Leaf Spot	1100
Bacterial Spot	1100
Leaf Mold	1100
Yellow Leaf Curl	1100
Spider Mites Two Spotted	1100
Tomato Mosaic Virus	1100
Target Spot	1100
Healthy	1100

2. **Image Pre-processing**

Before developing the model, we should devote a significant amount of effort to data pre-processing. Before being used for model training and inference, pictures must first undergo image pre-processing. This includes adjustments to the size, orientation, and colour.

We resized all the images from the dataset into the standard size (224,224). This size is the requirement of MobileNet. We have randomly enlarged the images by 30 %. In other words, we have zoomed in the images for better visibility of the features.

We also rotated the images and flipped the images. The images were rotated by the angles of 90°, 180°, 270°. Also, the images were flipped from left to right and top to bottom separately.

Brightness and contrast were adjusted randomly for making the model robust against various lighting conditions. Sharpness of the image was also increase randomly for enhanced feature visibility.

Finally, images were rescaled between 0 and 1.

3. **Feature Extraction**

There are various ways in which machine models help us for feature extraction.

One approach is to use the model as a feature extractor itself. This involves using a pre-trained model such as CNN. While we have used MobileNet.

Another approach is where during the feature extraction process the model acts as guide.

In both cases, the model plays a critical role in the feature extraction process by identifying relevant patterns and relationships in the input data. This can help improve the quality and relevance of the extracted features and ultimately improve the performance of the machine learning model.

4. **Crop disease detection and classification**

A computer model learns to do classification tasks directly from images, text, or sound using deep learning.
Models are trained using a large collection of data and network architecture having multiple layers.

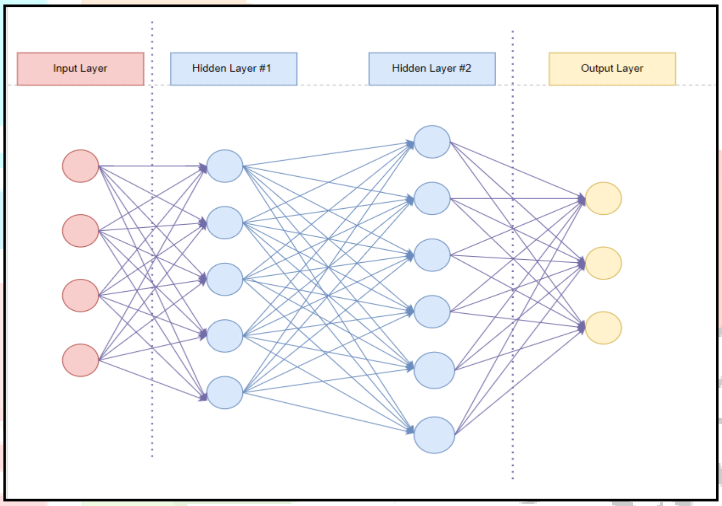

figure 10: deep learning network

A pre-trained model is used as an initial point for newer classifications while using a technique known as transfer learning. Transfer learning is the process of using a pre-trained model that has already acquired important features from a large dataset as a jumping off point for a new and related task using a smaller dataset.

IV. Experimental Results

Accuracy can be given as:

$$\text{Accuracy} = \frac{(TP + TN)}{(TP + FP + TN + FN)}$$

where,
True Positive (TP): The model has predicted True, and the actual value was also True.
True Negative (TN): Model has given prediction False, and the real or actual value was also False.
False Positive (FP): The model has predicted True, but the actual value was False.
False Negative (FN): The model has predicted False, but the actual value was True.

Loss (Categorical Cross Entropy) can be given as:

$$\text{Loss} = -\sum_{i=1}^{\substack{\text{output}\\ \text{size}}} y_i \cdot \log \hat{y}_i$$

where,
y_i is an actual value, and $\hat{y}_i$ is a predicted value

Table 3 Accuracy and Loss according to number of Epochs

Epochs	train_loss	val_loss	train_accuracy	val_accuracy
1	2.8672	0.5175	0.6582	0.8085
2	0.6213	0.4499	0.7862	0.8609
3	0.4932	0.3322	0.8327	0.881
4	0.4617	0.3164	0.8475	0.8901
5	0.4092	0.3601	0.8654	0.878
6	0.3885	0.3338	0.87	0.8891
7	0.359	0.2914	0.8792	0.9042
8	0.3594	0.2891	0.8817	0.9052
9	0.3413	0.3798	0.8881	0.875
10	0.3522	0.2947	0.8841	0.9083
11	0.3144	0.2671	0.9009	0.9183
12	0.3039	0.3148	0.8975	0.8952
13	0.298	0.3515	0.9037	0.8911
14	0.2802	0.3163	0.9097	0.9032
15	0.2907	0.3398	0.9082	0.8841
16	0.2737	0.2678	0.9128	0.9163
17	0.277	0.3404	0.9105	0.9083
18	0.2709	0.3198	0.9152	0.9113
19	0.2806	0.3177	0.9132	0.9022
20	0.2762	0.3	0.9115	0.9123
21	0.2563	0.3128	0.9188	0.9214
22	0.2425	0.2879	0.9256	0.9032
23	0.2472	0.4305	0.9217	0.8861
24	0.2528	0.3528	0.9236	0.8921
25	0.2436	0.3663	0.9266	0.9073
26	0.2203	0.3347	0.9335	0.9052
27	0.2207	0.3144	0.9296	0.9194
28	0.2455	0.2911	0.9287	0.9254
29	0.261	0.3203	0.9225	0.9224
30	0.2275	0.4216	0.9288	0.8871
31	0.228	0.2553	0.9338	0.9214
32	0.2161	0.3014	0.9332	0.9234
33	0.1978	0.2877	0.9366	0.9153
34	0.2181	0.3633	0.9324	0.9093
35	0.2198	0.3347	0.9323	0.9052

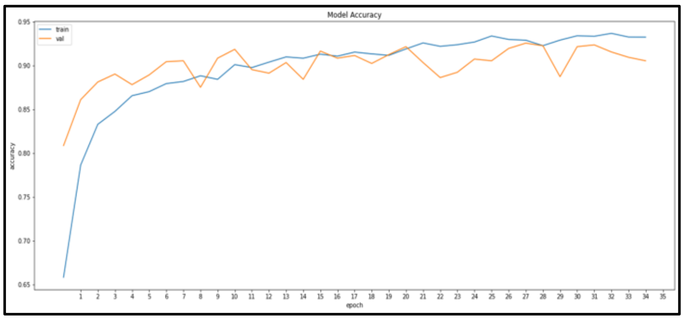

figure 11: epoch vs accuracy

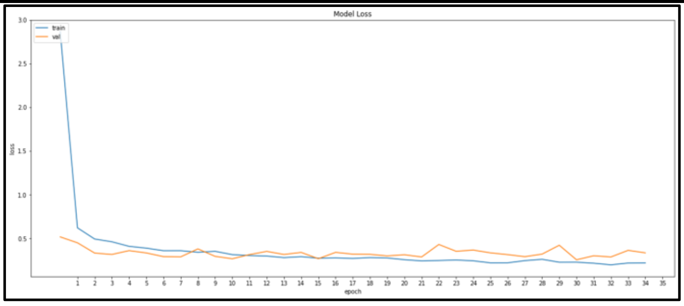

figure 12: epoch vs loss

V. CONCLUSION AND FUTURE WORK

Thus, a model built for the detection of the disease in the affected tomato crops is done and this proposed work is implemented by having Ten numbers of classes of tomato crop disease. Overall, this work has been implemented by using MobileNet architecture. The model in this work gives the training accuracy of 88.41%. and validation accuracy of 90.83%. Our future work can be to diversify the number of crops acceptable by the model using an open database (Plant Village).

REFERENCES

[1] S.Santhana Hari, Mr. M.Sivakumar, Dr. P.Renuga, S.karthikeyan, S.Suriya, "Detection of Plant Disease By Leaf Image Using Convolutional Neural Network", 2019 International Conference on Vision Towards Emerging Trends in Communication and Networking (ViTECoN), Vellore, India , ISBN:978-1-5386-9353-7

[2] Nikhil Patil, Rajab Ali, Vaibhav Wankhedkar, Prof. Deepali Nayak, "Crop Disease Detection using Deep Convolutional Neural Networks", International Journal of Engineering Research and Technology (IJERT), ISSN: 2278-0181, Vol. 8 Issue 03, March-2019.

[3] Sakshi Raina, Dr. Abhishek Gupta, "A Study on Various Techniques for Plant Leaf Disease Detection Using Leaf Image", 2021 International Conference on Artificial Intelligence and Smart Systems (ICAIS), ISBN:978-1-7281-9537-7 ,March 2021.

[4] Sharath D M, Akhilesh, S Arun Kumar, Rohan M G and Prathap C, "Image based Plant Disease Detection in Pomegranate Plant for Bacterial Blight", International Conference on Communication and Signal Processing, ISBN:978-1-5386-7595-3,April 4-6, 2019, India.

[5] Prakanshu Srivastava ,Vibhav Awasthi ,Vivek Kumar Sahu,Pawan Kumar Pal, "Plant Disease Detection Using Convolutional Neural Network", International Journal of Advanced Research,ISSN: 2320-5407, January 2021.

[6] Sona Vijayan, Prameeja Vimal "DETECTION OF PLANT DISEASE USING IMAGE PROCESSING TECHNIQUES".International Journal of Creative Research Thoughts ,Volume ISSN: 2320-2882, 9, Issue 6 June 2021.

[7] Anuradha Badage, "Crop Disease Detection using Machine Learning: Indian Agriculture", International Research Journal of Engineering and Technology (IRJET) ,Volume: 05 Issue: 09, Sep 2018 , p-ISSN: 2395-0072 | e-ISSN: 2395-0056.

[8] Manivarsh Adi, Yeshwanth Kumar , Abhishek Kumar Singh , Harinath Reddy A ,Pooja Rana, "An Overview on Plant Disease Detection Algorithm using Deep Learning" , 2021 2nd International Conference on Intelligent Engineering and Management (ICIEM)

[9] Tingzhong Wang, Honghao Xu, Yudong Hai, Yutian Cui, Ziyuan Chen, "An Improved Crop Disease Identification Method Based on Lightweight Convolutional Neural Network", Hindawi Journal of Electrical and Computer Engineering Volume 2022.

[10] G. Madhulatha , O. Ramadevi , "Recognition of Plant Diseases using Convolutional Neural Network" , Proceedings of the Fourth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC), IEEE Xplore Part Number:CFP20OSV-ART; ISBN:978-1-7281-5464-0

[11] Prajwal Gowda B.S , Nisarga M A, Rachana M, Shashank S, Mrs. Sahana Raj B.S, "Paddy Crop Disease Detection using Machine Learning", International Journal of Engineering Research and Technology (IJERT),ISSN: 2278-0181, NCCDS - 2020 Conference Proceedings

[12] Ebrahim Hirani, Varun Magotra, Jainam Jain, Pramod Bide, "Plant Disease Detection Using Deep Learning", 2021 6th International Conference for Convergence in Technology (I2CT)Pune, India, Apr 02-04, ISBN:978-1-7281-8876-8 2021