

Tomato Crop Disease Detection and Pest Management

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Abstract:

Agriculture field plays a vital role in India as most of the population depends on it. To strengthen the agriculture field research on various topics related to that field is very important. Leaf disease is one of the major area where lot of work need to be done. This paper proposes an idea to detect tomato disease using tomato leaf and suggests the pesticide as a remedy. The proposed system provides tomato diseases detection and pesticide management application. Farmers can capture an image of tomato leaf and then application detects the accurate disease and suggests pesticide accordingly. The system also provides alerts if certain tomato disease is spreading in an area due to various environmental or ecological factors. The proposed system is developed using convolution neural network (CNN) for disease detection. The Plant Village Dataset and Rashtriya Chemical Fertilizers (RCF) Datasets are used to validate the proposed system. These two datasets includes colored and grayscale images of Village Dataset and Colored Images of RCF Dataset. The overall average accuracy achieved by considering above three types of images is 94.66%.

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INTRODUCTION:

The motivation for this system is primarily an interest in undertaking a challenging and interesting area of research, as well as we used to live in agriculture dependent country like India, and our responsibility is to do something for our society. Farmer cultivates the eatable products for the rest of population living in the urban areas. For more production, there is need to resist the plant diseases. But the pharmacist misguides the farmers by giving the excessive and unwanted amount of fertilizers, pesticides. Plant diseases can be of leaf diseases, stem diseases or diseases due to instability in the weather. Now a day's crop faces many diseases.

The medical pharmacist observes the crop and detects as well as identifies the disease from his naked eye observation. But this method is very costly as it requires expert observation in constant manner. Now a day's, these experts used to cheat

with farmers. They used to give excessive dosage of drugs, pesticides and fertilizers than what it requires actually, sometimes they used to misguide the farmers due to their greedy approach towards money. The excessive dosage of pesticides and fertilizers may affect the fields for lifetime, or it may leads to drastic reduction in the production.

The plant disease recognition aids for getting benefits in various ways. It detects plant diseases and also suggests the best suitable dosage of organic/inorganic drugs, pesticides and fertilizers. For the detecting diseases on the crop plant early and accurately we can use image processing techniques.

The system will be mainly focusing on the following:

- Plant Disease diagnostics
- Efficient classification of diseases according to crops.

- Suggest suitable fertilizers and pesticides.

RELATED WORK

Lot of work is going on the tomato plants to detect different diseases using different machine learning algorithms. Authors Shijie, J., Peiyi, J., Siping H., & Haibo, L. (2017) used VGG16 [2] for feature extraction and SVM for classification. They apply it on diseased colored leaf images of tomato plants and got 89% of accuracy

Authors Mohanty, Hughes, & Salath, 2015 tried two different deep learning network architectures AlexNet [3] and SqueezeNet [3]. AlexNet combined feature extraction and classification. SqueezeNet required less memory than AlexNet. The accuracy of AlexNet was good but SqueezeNet was more suitable for portable devices. Experimentation done on the photos of tomato leaves and detected the different diseases.

Authors Durmuú, H., Güneú, E. O, and Kõrcõ, M. (2017) used AlexNet[3][4] and GoogleNet[4] to train the classifier. AlexNet done both the jobs such as feature extraction from leaf images and then classified it to the correct disease class. GoogleNet was used to detect 7 diseases. As it was a very good CNN architecture and provides better accuracy they developed the models and hardened on PlantVillage dataset. It gives accuracy of 85.53% and 99.34% respectively.

Authors YANG, S., GUO, J., ZHAO, J., & WANG, H. (2009) used acoustic emission [8] sensors which captures the stress of the diseased crop. An automatic detection system captures those acoustic signals and detects the corresponding disease. On the other hand Shifeng, Y., Long, X., & Jimin, Z. (2014) used PCI-2 [9] acoustic emission board and sensor R15 to catch the emission signals of the stress diseased plant. AEWIN software and virtual instrument technology shares the information between acoustic emission and diseased crop plant. It helps to detect precise disease and cure of the tomato plant.

Authors WANG, X., YANG, S., & ZHANG, C. (2009) used machine software which read the water stress and acoustic emission signals [10] from tomato leaves. Data acquisition system helped the software to collect the data. The mathematical model was developed which provides irrigation control and actual source location. The model takes care of the noise influence and ultrasonic signals and extract frequency signals which were very high. The system was analyzed and proved for good accuracy.

The analysis of these methods is given below in Table I.

Table I Comparison of Disease Detection using Deep Learning

Parameters	Paper1 [2]	Paper2 [3]	Paper 3 [4]
Algorithm used	VGG16, SVM, Fine Tuning	AlexNet, SqueezeNet	AlexNet, GoogleNet
Use of Algorithms	VGG16: feature extraction SVM, Fine - Tuning: Classification	AlexNet: classification SqueezeNet: classification	AlexNet: classification GoogleNet classification
Advantages	It was one of the earliest attempts to use CNN's in image processing . This helps to boost accuracy	Alexnet combined feature extraction and classification. SqueezeNet required less memory	Alexnet combined feature extraction and classification. GoogleNet outperformed any other CNN

	as features were selected by VGG16.	than alexnet.	before it.
Disadvantages	Results were heavily dependent on quality of image taken.	AlexNet was one of the earliest CNN architectures. Although SqueezeNet is small it's accuracy is not good.	GoogleNet was used to only detect 7 diseases.

PROPOSED SYSTEM

User registers him in our application. User provides its personal details like name, mobile number, email id, etc. Once the user has been successfully registered, user can login to the application. User has an option to upload leaf image through gallery. Once the image is uploaded it gets stored on the MySQL database as shown in fig. 1.

1] CNN-Inception V3: Trained on dataset, containing leaf images of tomato. The model expects the images to be stored in TFRecords. The features considered by Inception V3 are shape, size, color, etc of the tomato leaf.

2] Learning: Inception V3 is trained on Plant Village dataset which contains around 14000 tomato leaf images. Using this images Inception V3 learns the features required to identify diseased tomato crop.

3] Feature Extraction: Inception V3 contains inception module which extracts features required for classification purpose. It uses features such as shape, size, color, spots etc.

4] Pre-Processing: Preprocessing is required to remove noise from images. Preprocessing such as removing the background and converting the image into grayscale is done to increase accuracy.

5] Classification: This extracted features were used for classification of new tomato leaf images. Classification gives diseased class for that leaf image.

6] Comparison: Comparison is done for output of various disease classes and final class is decided with highest probability.

7] Diagnosis: Final diagnosis report is presented to user which includes disease class of leaf image. It also includes pesticide to be used for the disease. During in which time span pesticide must be used is also presented to the user. Alerts are generated if there are any.

8] Testing: Testing is done on new leaf images to identify disease class on new leaf images. Testing includes activities such as taking image, preprocessing it and then giving it as input to classification stage.

9] Pesticide suggestion: Based on disease detected, pesticide is suggested by the system which will help farmer from spreading that disease to other plants and save his crops.

10] Alert system: If a disease is detected in an area above a threshold value then it is a indication that the atmospheric conditions is favorable to that disease. Hence all farmers in that area are alerted about spread of that disease and given proper precautions to stop that disease.

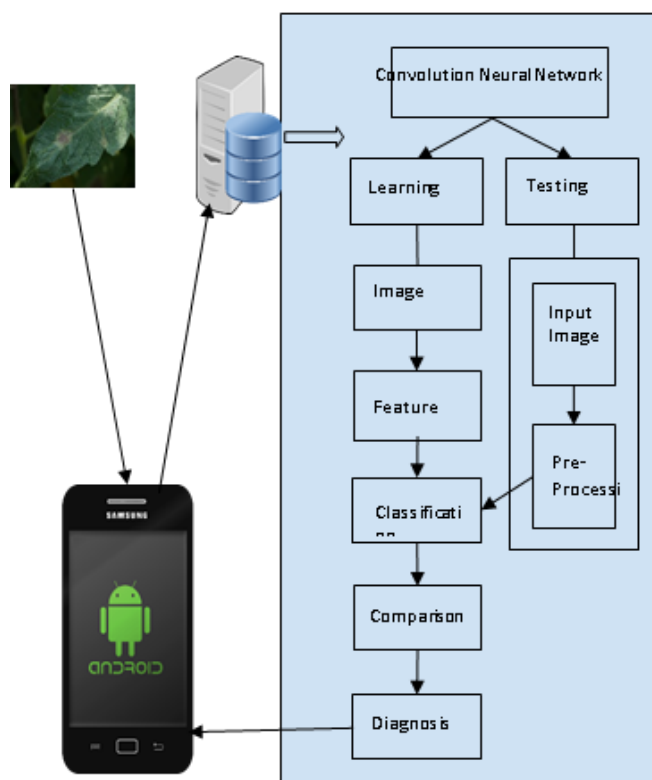


Figure 1. System Architecture

dataset and other dataset we collected is from Rashtriya Chemicals and Fertilizers (RCF) company

[A] PlantVillage Dataset [11]

PlantVillage dataset contains 14828 leaf images of tomato crop. There are total 9 disease classes such as early blight, late blight etc. Size of the image is 12-15 kb. It contains both gray scale and colour images. Dimension of the image is 256*256. Sample images are shown in fig. 2

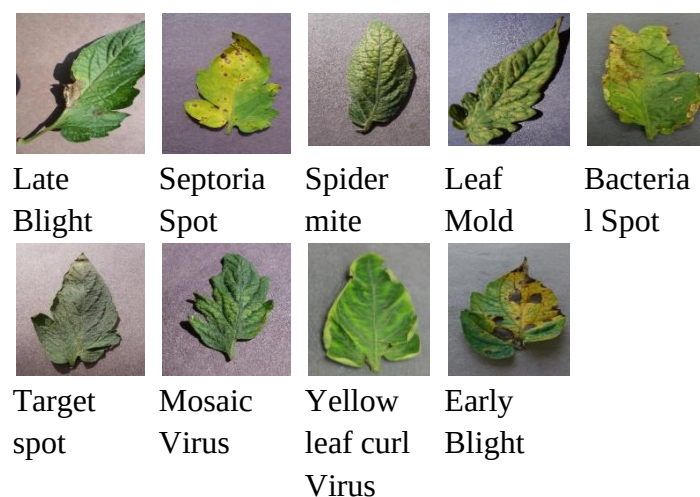


Figure 2. Images showing diseases in Plant Village dataset

[B] RCF Dataset

Rashtriya Chemicals and Fertilizers (RCF) dataset contains 5 diseases. Database size is 2.5 GB and Number of Images are 5743 (Color Images). Sample images are shown in fig. 3.

Experimental Setup:

Hardware and software requirements: -

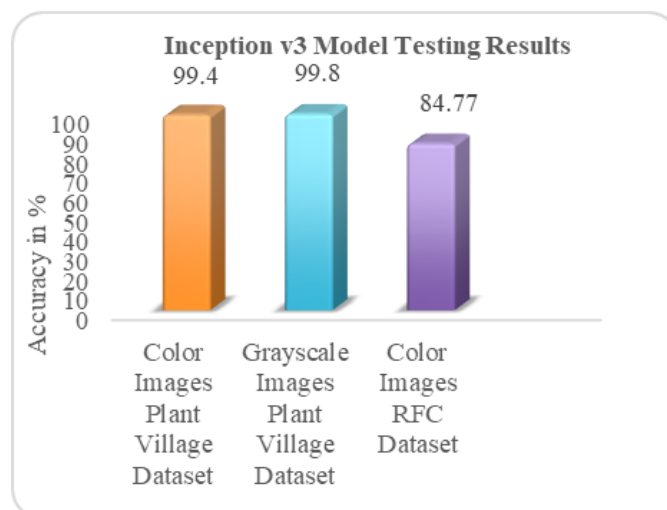
Hardware requirements for this system are processor with high GPU and clock rate. Ram more than 4 to 8 GB is required. we will be using python along with tensorflow and keras deep learning frameworks.

GoogleNet Inception v3 Training Parameters:

- (1) Transferred learning is used with GoogleNet V3.
- (2) Batch Size :- 32.
- (3) Learning Rate :- 0.001.
- (4) RMSProp function is used for optimization.
- (5) Epoch's after which learning rate decays :- 30.
- (6) Learning rate decay factor :- 0.16.

Dataset Used:

We have used one dataset for training and 2 datasets for testing. First dataset is PlantVillage



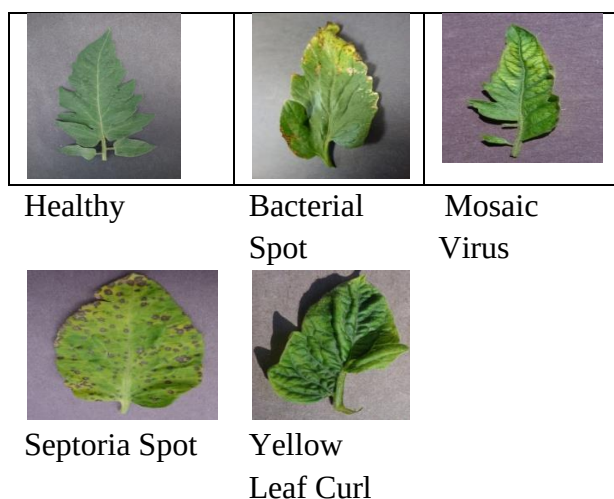


Figure 3. Images showing diseases in RCF dataset

Selection of Tomato Crop Images from Plant Village

Dataset

- Images are divided such as 80% are used in training, 10% are used in cross validation and 10% are used in testing data.
- Training data :- 11863 images.
- Cross validation data :- 1482 images.
- Testing data :- 1483 images.
- Images are converted into TFRecord format.

RESULTS AND DISCUSSION

We have trained the model 2 times for comparison. First time we have trained model on color segmented images of PlantVillage dataset and tested on it. Second time we have trained our model on grayscale segmented images of PlantVillage dataset and RCF dataset.

From the above bar graph shown in fig.4, it is clear that the accuracy of color images are less as compared to the grayscale images. The maximum accuracy achieved is 99.8% using the Grayscale images of Plant Village dataset. The minimum accuracy achieved is 84.77% using the Colored images of the RFC dataset. The overall Average

accuracy achieved by considering above three types of images is 94.66%. Considering the colored and grayscale images of Plant Village Dataset the accuracy achieved is more for gray scale images. The training curve to the model is as shown in fig. 5.

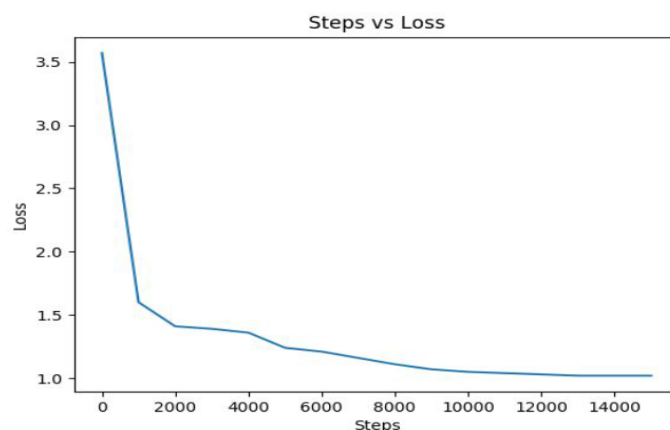
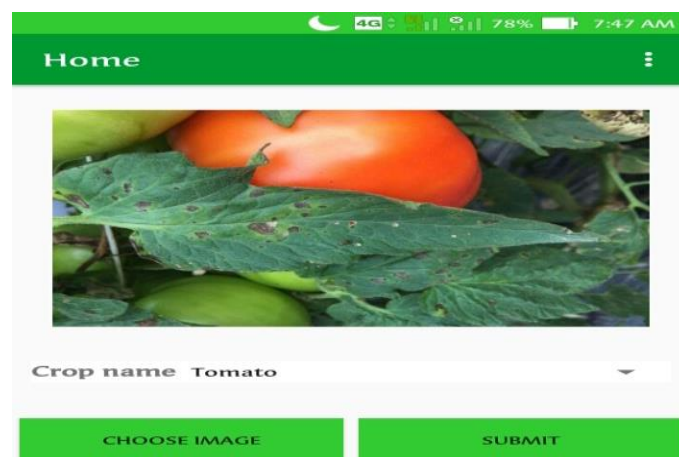


Figure 5. Training Curve of Inception v3 GoogleNET Model

The android app developed for the system is shown below.

Application Homepage



Disease Prediction Result

Prediction results

Category: late_blight
Probability: 99.99%
Pesticide: Copper_based_fungicides

Category: yellow_curved
Probability: 0.0%
Pesticide: Imidacloprid_Spray

Category: bacterial_spot
Probability: 0.0%
Pesticide: Sulfur_based_fungicides

Category: septorial_leaf_spot
Probability: 0.0%
Pesticide: Copper_based_fungicides

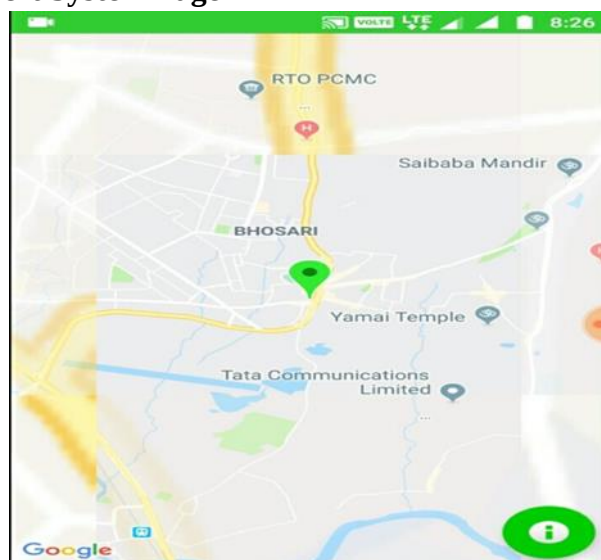
Category: leaf_mold
Probability: 0.0%
Pesticide: Chlorothalonil_compound

CANCEL
SAVE

Disease Detection Records Page

History	
	Category: mosaic_virus Probability: 72.78% Time: Tue Apr 16 08:09:15 GMT+05:30 2019
	Category: late_blight Probability: 100.0% Time: Tue Apr 16 08:08:49 GMT+05:30 2019
	Category: septorial_leaf_spot Probability: 99.98% Time: Tue Apr 16 08:08:26 GMT+05:30 2019
	Category: mosaic_virus Probability: 34.92% Time: Tue Apr 16 08:07:16 GMT+05:30 2019
	Category: late_blight Probability: 99.99% Time: Tue Apr 16 07:42:07 GMT+05:30 2019
	Category: late_blight Probability: 99.99% Time: Tue Apr 16 07:41:05 GMT+05:30 2019
	Category: late_blight Probability: 99.99% Time: Mon Apr 15 21:28:59 GMT+05:30 2019

Alert System Page



CONCLUSION:

We have developed an effective Android application to help farmers to detect disease and use correct pesticides for accurate duration in order to protect the tomato crop. This Android application will help farmers through its crop epidemic alert system, so that the farmer will be well prepared in advance to face the crop epidemic. We found that Colored images give less accuracy than grayscale images when trained. Colored images give less accuracy because lighting condition and brightness affects training, on the other hand there is no effect of lighting condition in which image is taken for grayscale images.

Considering the colored and grayscale images of Plant Village Dataset the accuracy achieved is 99.4% and 99.8 respectively. Colored images of RFC dataset gives testing accuracy of 84.77%. The GoogleNET Inception v3 is the most accurate and effective architecture for disease detection and pesticide management.

VI. FUTURE SCOPE

In future we will like to add forums for farmers and visualization for part of tomato leaf which was affected so that farmers can understand difference between healthy plant and diseased plant. We would also like to expand this work to other plants.

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