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Different Plant Disease Detection and Pest Control Techniques Using Image Processing

Nanda Barthare[1], Dr. Abhilasha Mishra[2], Prof. Sarita Verma[3]
[1]PG Student, [2]Head of Department, 3Assistant Professor, Department of Electronics and Telecommunication Engineering., Maharashtra Institute of Technology, Aurangabad(MS), India

Abstract: Tomato is one of the most important fruit vegetable in our daily life. 80% of kitchens uses Tomato. but there are some diseases and some disorders on the tomato plant. To overcome this problems many of technologies are used. Such as image processing , feature extraction ,feature classification are used as traditional method, also the end to end structure is used to simplified recognition process and overcome problems. Here we are using the deep learning method for object detection .it saves time and effort .also it gives the accuracy to reduce the huge losses caused by diseases and pest.in deep learning method Convolutional Neural Network (CNN) is used. the datasets are the real images of tomato plants are taken. Through the above research the identification and detection of disease of tomato plant is quickly done. It is an engineering application for plant disease detection and pest control.
Keywords: CNN architecture, deep learning, machine learning, plant village datasets.

I. INTRODUCTION

The constant growth of economy and society has caused global climate and environmental problems. The existence of diseases and bug pests seriously affects people's life. The frequency and occurrence of plant diseases and bug pests is higher and better and more complex (Food and Agriculture Organization of the United Nations). Therefore, it is very important to study the avoidance of plant diseases and insect pests, as well as the diagnosis andremedial measures of plant diseases and insect pests. Tomato is a few of the important economic crops, which not only contains rich vitamins, but can also be used as fruit. In recent years, with the recognition of Western food, spaghetti sauce is more and more popular. The demand for tomato is increasing, and it's gradually become a crucial food in people‟s lifestyle . Therefore, tomato plays a particularly important role in agricultural vegetable production and vegetable trade. As one of the foremost widely cultivated vegetables within the world, tomato has not only high yield, wide adaptability, but also high nutritional value. during its growing period, illnesses and pests. The illnesses/diseases that affect tomatoes. They include tomato leaf ,roots, fruits of tomato plant .the diseases are causes decrease in growth ,production of tomato. The diseases that affected to tomato plants are as follows:

1.Tomato target spot 2. Tomato mosaic virus 3.Tomato yellow leaf curl virus


Figure 1


Figure 2


Figure 3

4. Tomato bacterial spot 5.Tomato early blight 6. Tomato late blight


Figure 4


Figure 5

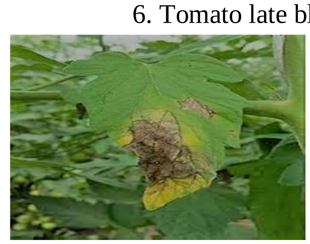
Figure 6

7. Tomato leaf mold

Figure 7

8.Tomato septorial leaf spot

Figure 8

9. Tomato spider mites two spot

Figure 9

Impact on the incidence of tomato diseases and pests. The conventional way of artificially detecting diseases and bug infestations is entirely dependent on the grower's skill with observation or consulting specialists. Such a method is not only inefficient, expensive, subjective, inaccurate, and time-consuming; it is also slow. The use of data technology in conjunction with the ongoing development of the web offers fresh ideas and approaches for identifying agricultural diseases and insect pests. Technology for accurate image recognition can increase the effectiveness of Image recognition lowers the value and increases the accuracy of popularity. Therefore, a great deal of research has been conducted by professionals and students both domestically and internationally, with a particular emphasis on deep learning. The use of deep learning in the diagnosis of crop diseases and insect pests can significantly reduce the effort and cut identification time. The two most crucial aspects of deep learning are its complex network architecture and massive data samples. Strong technical assistance for picture recognition is now available thanks to the development of deep learning technologies.

II. LITERATURE SURVEY

1 The tomato is one of the most significant fibre crops, and it is especially important in India for people to come together on a social and economic level. However, if diseases like Alternation Tomato Spot and a lack of certain essential nutrients go undetected, the production could be reduced by up to 25%. Farmers may find it marginally advantageous to lengthen the crop's assembly in order to reap greater financial rewards. The "Alternation Tomato Spot" disease is the most serious and frequently observed disease on tomato plants in India, hence it has received special attention in this study. During this research, deficiencies of important nutrients like nitrogen, potassium, phosphorus, manganese, molybdenum, chloride, and calcium were also found. The system's whole operating flow has been proposed. The best algorithms are specific and are changed as necessary. Algorithms for detection include colour histogram and template matching. There has been thorough analysis and comparison. Results and a conclusion have been reached after running the code on a substantial number of tomato photos collected from various locations. Results demonstrate how this research is more practical and beneficial than prior studies [1].

During a research of identifying and diagnosing tomato disease, the pattern of disease is vital part. In that, various features of the pictures are extracted viz. the colour of actual infected image. There are numerous diseases occurred on the tomato therefore the tomato color for various diseases is additionally different. There are various other features associated with shape of image which are different shape of holes on the tomato. Generally the tomato of infected image has elliptical shape of holes, so calculating the main and axis is that the major task. The features might be extracted using self-organizing feature map along side a back- propagation neural network. This information is employed to segment tomato pixels within the image [2].

The detection of disease on a tomato is completed in number of steps by the proposed system. Firstly the first True-color image transformation is completed into HSV which may be a color descriptor structure where hue component is employed for further analysis. Next, green color masking is performed by assigning zero or some background value to the green pixel which isn't our part of interest. Thus segmentation is completed and useful segments are obtained which contains significant amount of data. For texture feature analysis, color co-occurrence method is employed by computing the parameters of Spatial Gray-level Dependence Matrices (SGDM) like Contrast, Energy, Local homogeneity and correlation for hue content [3]. In agriculture research, automatic tomato disease detection is important research topic because it may prove benefits in monitoring large fields of crops, and thus automatically detect symptoms of disease as soon as they seem on plant leaves. The term disease is typically used just for destruction of live plants. This review paper provides various methods wont to study of tomato disease detection using image processing. The methods studies are for increasing throughput and drop subjectiveness arising from human experts in detecting the tomato disease. Digital image processing may be a technique used for enhancement of the image. to enhance agricultural products automatic detection of indicators is useful [4].

Authors present a survey on the various sorts of tomato diseases in plants and their identification process. An identification problem deals with associating a given input form with one among the distinct classes.
Plant tomato disease identification may be a technique where tomato spot disease is identified supported its not an equivalent morphological features.
There are different successful identification techniques like Probabilistic Neural Network, Genetic Algorithm, Back Propagation Neural Network and Principal Component Analysis (PCA). Choosing the tactic for identification is usually a difficult task because the standard of the results are often varying for various input file. Plant tomato disease identification has wide uses within the field of Agriculture to extend the productivity.
The goal of this survey is to supply a summary of various identification techniques for plant tomato disease and provides the overall approach which uses these techniques [5]

III. BLOCK DIAGRAM IOT BASED CROP DISEASE DETECTION AND PEST CONTROL

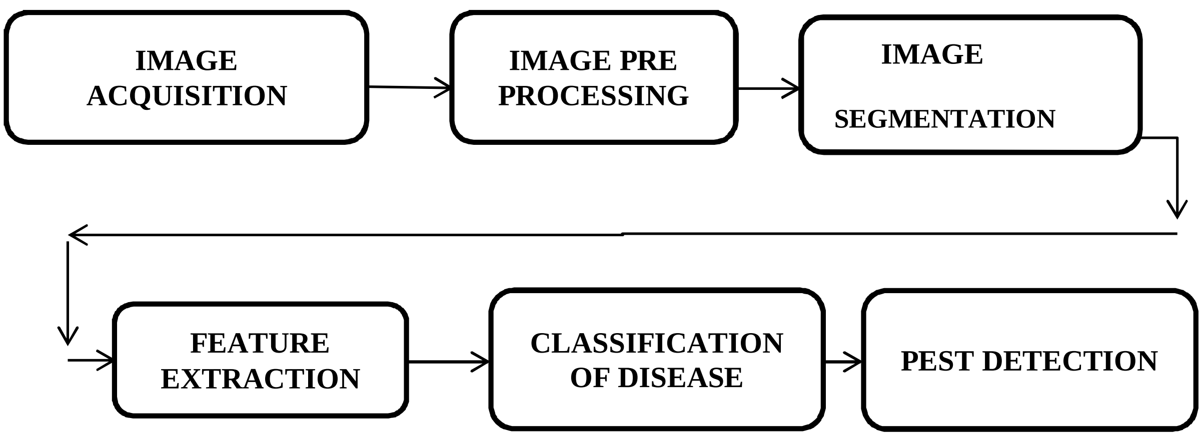

Figure 1. Block Diagram of IOT based crop disease detection and pest control

First, a digital camera is used to capture photographs of various leaves. Then, on the obtained images, image-processing techniques are used to extract valuable features required for further research. Segmentation is used to isolate the object of interest following pre-processing. In order to diagnose disease, the segmented part's characteristics are chosen, and then classification is completed.

IV. METHODOLOGY

Deep learning is used for the training dataset which is actually a dataset of real images taken from camera. More than three thousand images are trained. It is the part of machine learning methods which is based on artificial neural networks. the dataset used for the project is divide Into validation dataset 20% and training dataset as 80%.software configuration are as follows.

1) Memory used of the system is 32GB.
2) Disk used for the project is 1 TB.
3) Computing processing unit i.e CPU's are of Dual Intel Xeon Platinum 8268s cascade lakes @2.9GHz X48 cores
4) The GPU and CPU are both used for the project.GPU are more faster than CPUs.So the GPU's Dual NVIDIA VOLTA V100.used.
5) Operating system of Laptop/Desktop used Windows 10 is used.
6) The 3.6.5 PYTHON version is used for the program.
7) Tensor flow version 2.4.0 and CUDA11.03 is used.

V. FLOW CHART

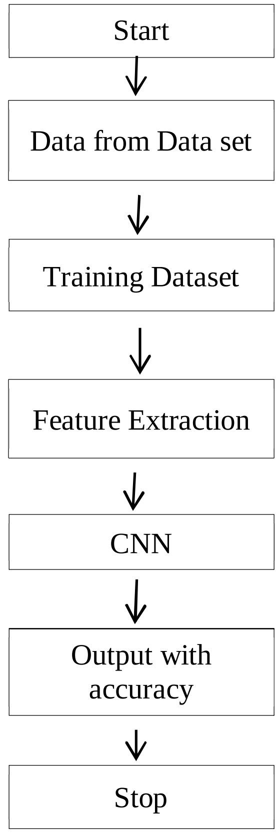

Figure 10. Flow Chart Of IoT Base Crop Disease Detection And Pest Control

VI. MATHEMATICAL FORMULATION

1) Accuracy

Accuracy is the most popular and straightforward metric for determining how many accurate predictions were produced based on the data, but we must first ask ourselves many questions: When determining a model's performance, does accuracy always perform well, and under what circumstances could accuracy not be the best statistic to use? To put it briefly, accuracy may not be a reliable sign of an unbalanced dataset. The accuracy of this model will be 99.9 percent, for instance, if the dataset has 999 negative samples and 1 positive sample, which is a well-balanced combination. The dataset only has one positive sample, so the result is not accurately evaluated for the positive categories. If the positive result in this case reflects a carrier, the result may also be deceptive and expensive. The percentage of forecasts that are right is how accuracy is defined here. Similar to the last example, accuracy cannot fully describe an unbalanced dataset, and alternative evaluation measures, such as precision, recall, or F1scor, should be taken into account .

$$\text{Accuracy} = \frac{\text{Corrected Predection}}{\text{Total Samples}}$$

2) Precision

Precision is defined as the fraction of true positives examples among the total recovered positive instances true positive (TP) + false positive (FP)). The sort of precision is between 0and 1, and can be calculated as below:

$$\text{Precision} = \frac{TP}{TP+FP} \quad 100\%$$

As the formula suggested, the precision metric evaluates the number of real positive prediction within total predicted positive samples and only need to take into consideration if false positive (A or Type I error rate) is significant to the study.

3) Recall

The recall is defined as the proposition of TP samples amount the total true positive (TP + false negative) (FN))and is also known as sensitivity or True Positive Rate (TPR). The range of recall is also between 0 and 1, and can be calculated as following equation

$$\text{Recall} = \frac{TP}{TP + FN}$$

4) F1 Score

F1 score is a weighted harmonic mean of recall and precision and had been usually used for manymachine learning algorithms. The equation is defined below:

$$F1 = \frac{2\ \text{Precision} \cdot \text{Recall}}{\text{Precision} + \text{Recall}}\ 100\%.$$

A. Convolutional Neural Network

Convolutional Neural Networks, shortened as CNN, has a complex network structure and can perform complication operations. The convolutional neural network model is composed of input subcaste, complication subcase, pooling subcases, full connection subcase and affair subcaste. In one model, the complication subcaste and the pooling subcaste alternate several times, and when the neurons of the complication subcaste are connected to the neurons of the pooling subcaste, no full connection is needed. CNN is a popular model in the field of deep literacy. The reason lies in the huge model capacity and complex information brought about by the introductory structural characteristics of CNN, which enables CNN to play an advantage in image recognition. At the same time, the successes of CNN in computer vision tasks have boosted the growing fashion ability of deep literacy.

The convolutional neural networks mainly have three layers. First one is input, the hidden layer and the last one is output layer. The hidden layer is called “hidden” because its input and output were masking activation function and final convolution. Number of input and outputs and channels are in the dot product to each other.as output of all passing through a layer ,it gives a feature map which is also called activation map.it have shape i.e height ,width, and channels in dot products. CNN is best because during convolution pooling it takes the data which have a grid, like images ,topologies, relation between separated featured. Let’s see how it works.

For example: 45*45*3=6075. that means for input image 45is height,45 is width and the are colour channel. The CNN produces the highest response with a local inputs which are spatially have patterns .very firstly CNN creates a representation of tiny parts of their inputs and then make them ready for representation of largest area. In poling layer it works on biggest number over four numbers.

An Example of Average Pooling and Max Pooling For CNN

15	16	12	6
0	10	18	12
8	8	14	6
4	12	12	8

Max pooling

16	**18**
12	**14**

Average pooling

10	**12**
8	**10**

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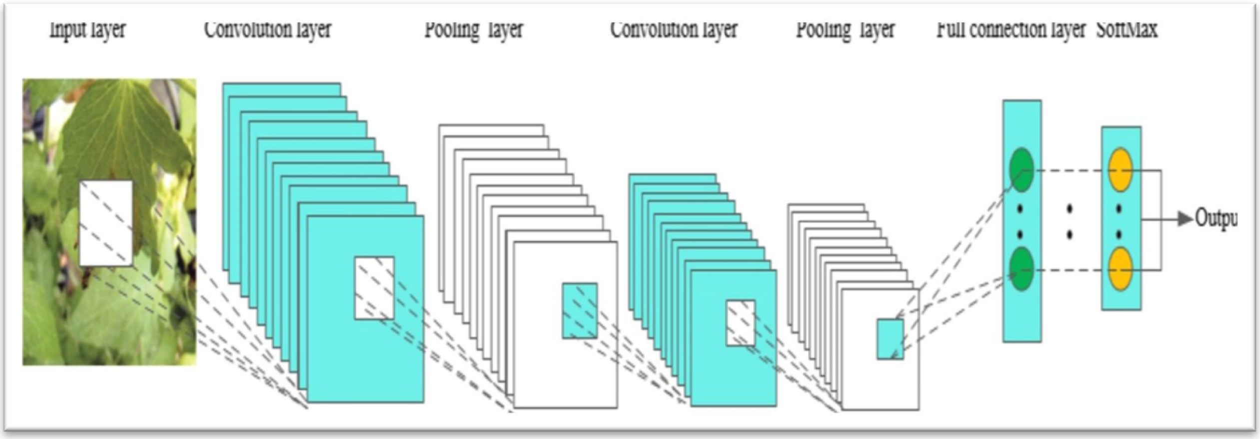

Figure 11. CNN Process

In the convolutional neural network the input layer is as original image upload which is taken from datasets. the convolution layer is formed for pooling. where the average pooling and the max pooling is done. After that again the convolution layer is formed and again the pooling layer is formed. And at the final stage we get the final output.

B. Comparison Between Deep Learning and Conventional Image Processing Techniques.

First, their Methods provide an explanation of the fundamental differences between manual design features + classifiers (or rules) and automatic learning of features from massive amounts of data. Methods for segmenting an image include threshold segmentation, region segmentation, and edge detection using Roberts, Prewitt, Sobel, Laplace, and Kirsh.

Feature extraction techniques include SIFT, HOG, LBP, form, colour, and texture. SVM, BP, Bayesian, and CNN, or convolutional neural network, are employed in the classification process. The conditions needed for traditional image processing techniques include a somewhat harsh imaging environment, great contrast between lesion and non-lesion areas, and little noise. High-performance computing systems and adequate learning data are other necessary criteria for deep learning. Examples of situations when conventional learning techniques can be used When the classification of a plant disease or pest changes, it is frequently essential to modify the threshold or the algorithm, which has poor recognition results in complicated natural environments. as well as for deep learning It is capable of adjusting to some intricate and genuine changes in the natural environment.

C. Dataset Preparation

The first aspect that must be taken into account to achieve good delicacy is not the model's construction. The training data's quality, together with its preprocessing and addition, is what can actually lead to the biggest improvements in delicacy. Thus, every procedure involving the administration of the data must be rigorously carried out. A clear description of the class taxonomy should be given at the start of the reflection phase, especially if the impurity intensity is annotated. This phase ensures the repeatability of the reflections. The risk of relying on the commentator is avoided by using more than one expert for reflection. Either addition operations or over fitting have been successfully avoided. They're entirely encouraged and simple to set up. It's still critical to carry out these. after being divided into training and confirmation subgroups, changes. If not, data leakage could result from a picture and its transformation ending up in training and confirmation sets.

D. Training and Evaluation Phases

Still, conducting several training sessions with the same hyper parameters can lead to bettered delicacy, as arbitrary initializations can have an impact on the results, If the time and computing coffers allow. When comparing hyper parameters, it would also be judicious to consider fixing the arbitrary number creators to help them from turning the comparison. Experimenting with further than one type of armature can also have a positive effect. For equal delicacy, choosing the least complex armature is more profitable from a functional point of view. However, transfer literacy is recommended to ameliorate calculation time and generalizability, If applicable. Formerly all the hyper parameters have been fixed, the model should be retrained by combining the images preliminarily used for training and confirmation into a global training set.

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VII. RESULT

As per discussion of the project, ,we get the results shown in above figure .the image is browsing from the google drive .at google drive we save the complete data sets which is in the images form that we have taken from digital camera. As the input is browsing image from the given datasets then processed and as output we get the detection of disease on the tomato plant. Also pest control for the same disease is also shown via message displayed at output. At the same time we get the E-mail which is registered in the code of project. It is always easy to handle the project from anywhere from the world. The healthy leaf for tomato plant is compare with the defected leaf . through the all process the disease is identified and the required remedies is also shown. the healthy ;leaf of tomato plant is as follows.

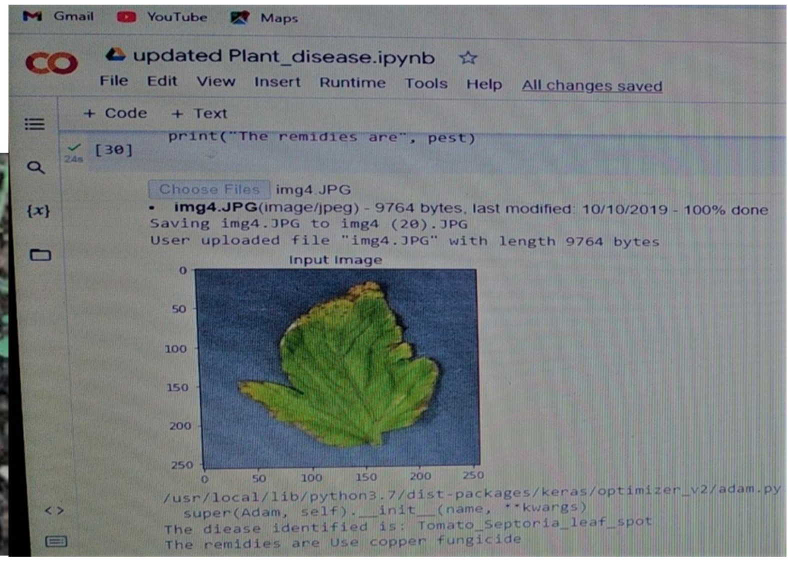

Figure 12 .Healthy leaf of tomato plant

Figure 13. Output of Project

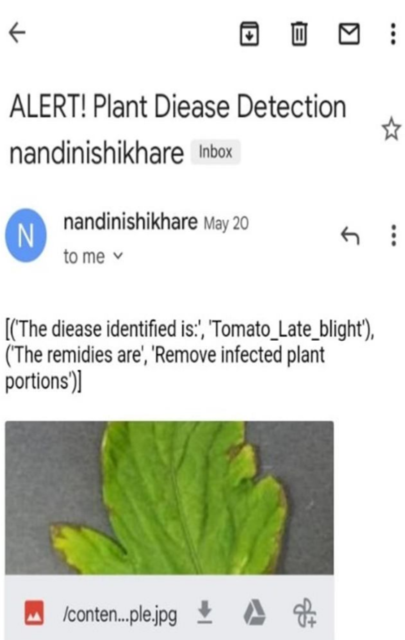

Figure 14

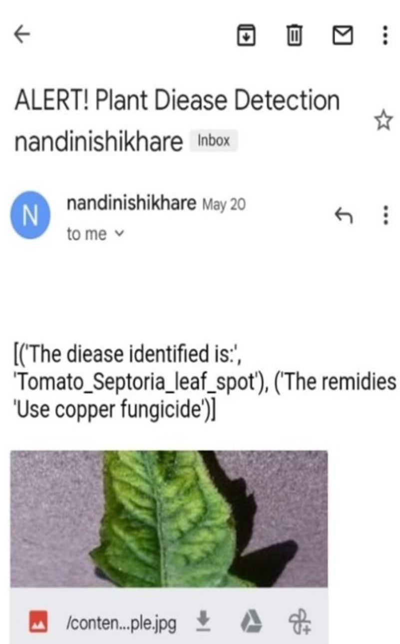

Figure 15

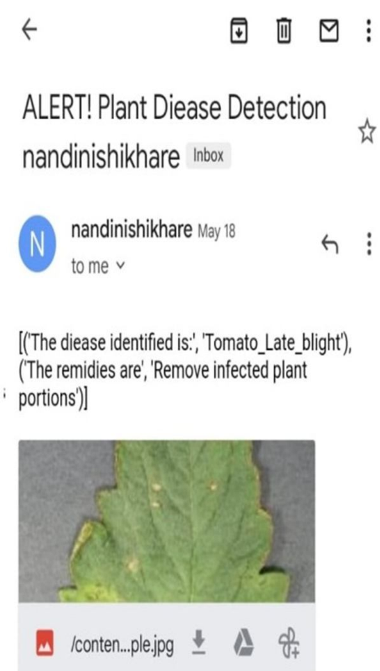

Figure 16

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The figure shows the actual browsing of the image at the run time of the project. The same output is get at the registered E-mail. The mailing system is actually use for the real time work. Now a days there is more chances of pandemic that time the contactless work for any agricultural officer is must. That time this system is work ideally**.**

Figure 17

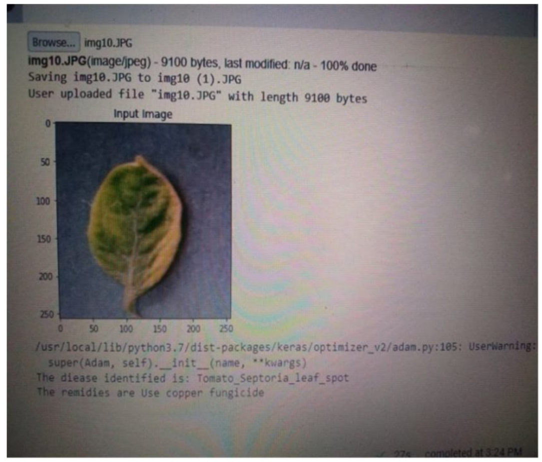
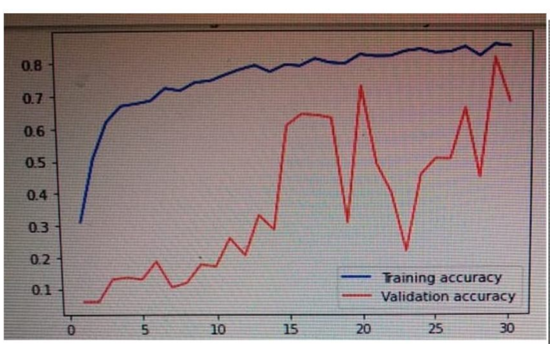


Figure 18

As output taken of the project shows the 98.99% accuracy. The disease identification of the tomato leaf is done by the project. Also the required remedies are shown in the message. Some output images shows the different diseases and their required remedies.

Email system is also the ideal part of the project. We can able to add the email of any authority which are working as agricultural department. This may get easy to work actual on ground level in any environmental condition.as we have the images as datasets of the plants.

A. Actual Graphical presentation of Training and Validation Loss



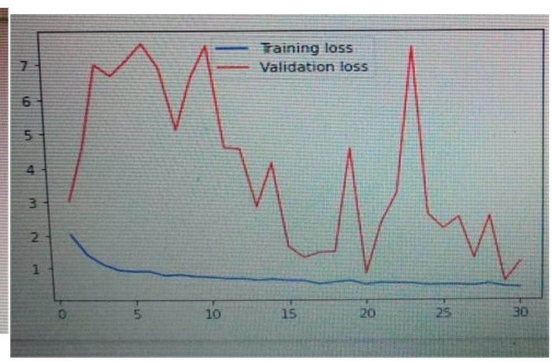


Figure 19

Figure 20

It is slightly vary while project is run ,at that time the speed of internet is affects the losses.

VIII. METHODS ADVANTAGES AND DISADVANTAGES

Using network as feature extractor we have the advantages of Obtaining effective lesion features. On other hand the disadvantage of method is Relying on other classifiers for final classification results. Original image classification have positive point is Classic in structure, it is also the basis of other classification network sub- methods and can refer to many existing networks. On other hand its negative point is Lesions need to account for a certain proportion in the image, otherwise their characteristics are easily pooled out, and generally only one class of lesion is allowed in an image Classification after locating ROI shows the advantages of obtaining ROI information of the lesions. and disadvantage is Additional methods are needed to obtain ROI. while going with Multi-category classification Solving sample imbalance to some extent but as disadvantage of method is Secondary training is needed. Sliding window is with positive point to Get rough localization of lesions in images but Sliding window size requires accurate selection, and can only get rough position, slow speed of traversal and sliding ,this is one of the disadvantage of that method. Heat map able to generate more accurate lesion areas but Accurate lesions location depends onnetwork classification performance which is drawback of method. Multi-task learning network is able to Combining other networks to obtain exact location and category of lesions simultaneously, and reducing the number of training samples required. But unable to support if the network structure is relatively complex, and a pixel-by-pixel label isrequired when adding segmentation branches.

IX. CONCLUSION

Plant diseases and pests detection methods based on deep learning combine them into end-to-end feature extraction, which has a wide range of development prospects and great potential. This is in contrast to traditional image processing methods, which handle plant diseases and pests detection tasks in several steps and links. A mature use in the real natural environment is still some distance away, and there are still some issues to be resolved, despite the fact that plant diseases and pests detection technology is evolving quickly and moving from academic research to agricultural application.

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