Plant Disease Detection using Image Processing

Anupama Mishra[1], Priyanka Chaurasia[2], Varsha Arya[3,4](✉), and Francisco José García Peñalvo[5]

[1] Himalayan School of Science & Technology, Swami Rama Himalayan University, Dehradun, India
[2] Ulster University, Northern Ireland, UK
p.chaurasia@ulster.ac.uk
[3] Insights2Techinfo, Bangalore, India
varshaarya21@gmail.com
[4] Lebanese American University, Beirut 1102, Lebanon
[5] Department of Informatics and Automation, University of Salamanca, Salamanca, Spain
fgarcia@usal.es

Abstract. Plant diseases have an impact on the development of their particular species, hence early detection is crucial. Numerous Machine Learning (ML) models have been used for the identification and classification of plant diseases, this field of study now appears to have significant potential for improved accuracy. In order to identify and categorise the signs of plant diseases, numerous developed/modified ML architectures are used in conjunction with a number of visualisation techniques. Additionally, a number of performance indicators are employed to assess these structures and methodologies.

Keywords: Plant disease · Machine learning

1 Introduction

India may be a cultivated country and concerning seventieth of the Population depends on agriculture. Farmers have large range of diversity for selecting numerous appropriate crops and finding the suitable pesticides for plant [4,6,8]. Hence, harm to the crops would end in large loss in productivity and would ultimately have an effect on the economy. Leaves being the foremost sensitive a locality of plants show illness symptoms at the earliest. The crops should be monitored against diseases from the terribly 1st stage of their life-cycle to the time they are ready to be harvested [10,12,14]. Initially, the manoeuvre accustomed monitor the plants from diseases was the quality eye observation that is a long technique that desires specialists to manually monitor the crop fields. inside the recent years, variety of techniques are applied to develop automatic and semi-automatic illness detection systems and automatic detection of the

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diseases by simply seeing the symptoms on the plant leaves makes it easier yet as cheaper. These systems have to this point resulted to be quick, cheap and a lot of correct than the quality technique of manual observation by farmers In most of the cases illness symptoms ar seen on the leaves, stem and fruit. The plant leaf for the detection of illness is taken under consideration that shows the illness symptoms. There are several cases wherever farmers do not have a completely compact data concerning the crops and conjointly the illness which will get affected to the crops. This paper could also be effectively utilised by farmers thereby increasing the yield instead of visiting the skilled and obtaining their recommendation. the most objective is not solely to discover the illness mistreatment image process technologies [17,18,20]. It conjointly directs the user on to Associate in Nursing e-commerce web site wherever the user should buy the medicine for the detected illness by comparison the rates and use befittingly in step r with the directions given. Greenhouse conjointly referred to as a building, or, if with enough heating, a Hodr house, could also be a structure with walls and roof created mainly of clear material, like glass, inside that plants requiring regulated atmospheric condition ar fully grown. As greenhouse farming is gaining a lot of importance currently a day's, this paper helps the greenhouse farmers in Associate in Nursing economical means. numerous techniques may be accustomed review the illness detection and discuss in terms of varied parameters. As per Figs. 1, 2 and 4, fungi, bacteria, and viruses causes most plant illnesses. Disease symptoms are obvious signs of infection [22–24]. Plant diseases cause visible spores, mildew, or mould and leaf spot and yellowing. Fungi cause plant diseases. Fungi infect plants by stealing nutrients and breaking down tissue. Plant diseases are prevalent. Plants show disease symptoms or effects. Fungi infections cause leaf patches, yellowing, and birdseye spots on berries. Some plant illnesses appear as a growth and mould on the leaves.The paper is organized into the following sections. 1st section provides a quick introduction to the importance of illness detection. Second section discusses the current work disbursed recently throughout this space and conjointly reviews the techniques used. Section 3 includes methodologies utilized in our paper. Section 4 shows the experimantal details, Sect. 5 discussed the results and performance analysis and lastly, Sect. 6 concludes this paper along with future directions.

2 Related Work

Alternia leaf spot, brown spot, mosaic disease, grey spot, and rust impact apple productivity. Current analysis lacks proper and timely detection of apple diseases to ensure apple trade health. SSD, DSSD, and R-SSD are object detection algorithms with two parts: the pre-network model, which extracts basic options. The opposite is a multi-scale feature map-using auxillary structure [1,2]. There are many machine learning techniques that are used to solve many real world problems [3]. Using square geometrician distances, Kmeans segmentation divides the leaf picture into four groups. Color Co-occurrence technique is used to extract colour and texture features [7]. Abuse classification uses neural network detection and rule-based backpropagation. System disease detection and

Fig. 1. Leaf infected by bacteria

Fig. 2. Leaf infected by virus

categorization accuracy was 93%. Observe leaf fungus on fruit, vegetable, cereal, and industrial crops. Every crop is grown differently [8]. For fruit crops, k-means agglomeration is the segmentation method employed, with texture options focusing on ANN [9] and closest neighbour algorithms to achieve an overall average accuracy of 90.6%. For vegetable crops, chan-vase segmentation, native binary patterns for texture feature extraction, SVM, and closest neighbour classification achieved an overall average accuracy of 87.9%. Mistreated grab-cut formula divides industrial crops. Ripple-based feature extraction has been utilised as a classifier with an 84.8% average accuracy. Mistreatment kmeans cluster and smart edge detector separate cereal crops. Extract colour, shape, texture, colour texture, and random rework. SVM Associate in Nursing closest neighbour classifiers achieved 83.6% accuracy. A processed image of a cold plant leaf shows its health. Their strategy is to limit Chemicals to the morbid cold plant. MATLAB extracts features and recognises images. This paper is preprocessed. Filtering, edge detection, morphology. Laptop vision expands the image classification paradigm. Here, a camera captures images and LABVIEW creates the GUI [12,19]. The FPGA and DSP-based system monitors and manages plant diseases. The FPGA generates plant picture or video for viewing and labelling. The DSP TMS320DM642 processes and encrypts video/image data. Single-chip nRF24L01 pair. Knowledge transfer uses 4 GHz sender. It uses multi-channel wireless connection to reduce system cost and has two data compression and transmission methods.

3 Proposed Methodology

The process of disease detection system primarily involves four phases as shown in Fig. 3. The primary part involves acquisition of pictures either through smart devices [11,16,21] such as camera and mobile or from internet. The second part segments the image [5,15] into varied numbers of clusters that completely different techniques will be applied. Next part contains feature extraction strategies and therefore the last part is regarding the classification of diseases. Imaging In this portion, plant leaf photographs are gathered using digital media like cameras, mobile phones, etc. with required resolution and size. Internet-sourced photos are also acceptable. The applying system developer loves image data formation. Image data boosts the classifier's effectiveness in the detection system's final stage. Segmentation This component simplifies an illustration so it's more significant and easy to investigate. This is the basic image processing strategy because of feature extraction. k-means agglomeration [13], Otsu's algorithmic method, and thresholding can segment images. k-means agglomeration organises possibilities into K categories. Minimizing the distances between objects and clusters completes the classification. Highlighting In this step, alternatives from the interest space must be extracted. These choices authenticate an image's meaning. Color, shape, and texture are supported. Most researchers want to use texture to detect plant diseases. Gray-level co-occurrence matrix (GLCM),

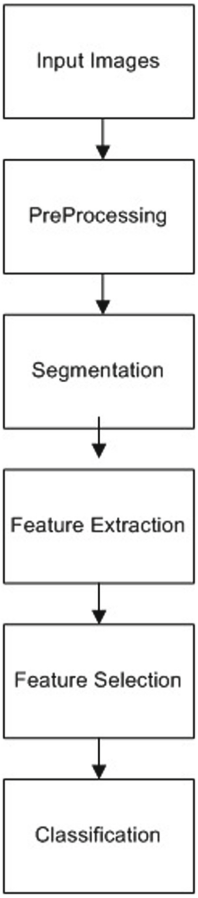

Fig. 3. Approach to classify the disease

colour cooccurrence approach, spatial greylevel idependence matrix, and bar graph-based feature extraction may be used to construct the system. GLCM classifies textures. Classification The classification section checks if the image is healthy. Some works classify unhealthy images into various disorders. For classification, MATLAB needs a classifier package routine. Researchers have used KNN, SVM, ANN, BPNN, Naive Bayes, and call tree classifiers in recent years. SVM is a popular classifier. SVM is an easy-to-use and reliable classifier.

4 Experimental Details

4.1 Experiment Setup and Data Sets

To implement the Machine Learning methods, the experiment was performed in the environment, which includes Python 3.10.4 64 bit on Jupyter Notebook

Fig. 4. Leaf infected by fungal infection

in Visual Studio Code with CPU: 11th Gen Intel(R) Core(TM) i5-1135G7 with Clock Speed @ 2.40 GHz–3.32 GHz , GPU RAM: 16GB DDR4, Storage: 1TB HDD with 256GB SSD. The scikit-learn, Matplot, Numpy, and Panda libraries were used through out the experiment and performance evaluation. The data set is collected from the email spam folder and normal mails.

5 Result and Performance Evaluation

Coaching and testing are distinct. One is in a research lab, where the model is tested with a constant dataset for training and testing. Field condition is the contrary, meaning our model was tested with $64000 world photos (land). Since the lighting circumstances and backdrop features of the $64000 field samples are different, our model may have a poor accuracy compared to the accuracy values in the science lab. To counteract this, we included a variety of photos in the training part (heterogeneity). For the evaluation of the performance in classification machine learning, we have the following metrics:

RECALL: how many spam emails recalled from all spam emails.

PRECISION: what is the ratio of email correctly classified as spam.

ACCURACY: it measures how many observations, both positive and negative, were correctly classified.

F1-Score: it combines precision and recall into one metric. The higher the score the better our model is.

ROC Curve: It is a chart that visualizes the tradeoff between true positive rate (TPR) and false positive rate (FPR). Basically, for every threshold, we calculate TPR and FPR and plot it on one chart. Of course, the higher TPR and the lower FPR is for each threshold the better and so classifiers that have curves that are more top-left side are better (Tables 1 and 2).

Table 1. Confusion matrix

Random forest		Naive Bayes	
842	1	834	9
25	271	2	294

Table 2. Classification report

Classifiers	Precision	Recall	F1 score	Accuracy
Random Forest	0.97	1.00	0.98	97.71
Naive Bayes	1.00	0.99	0.99	99.03

The accuracy of period detection of apple plant disease victimisation deep learning approach supported improved convolution neural networks is a smaller amount compared to the planned system as a result of it detects multiple diseases in an exceedingly single system.

6 Conclusion

This planned work is concentrates on the accuracy values throughout the $64000 field circumstances, and this work is reinforced by having many disease photographs. Therefore, an application that was developed for the detection of disease-affected plants and healthy plants has been completed. In general, this process is carried out from the ground up, and the results are very accurate. The work that has to be done in the long term is to increase the number of photographs that are present within the preset information and to update the design so that it is more accurate in accordance with the dataset.

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