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Image Processing based Plant Disease Detection and Classification

Ashima Uppal[1], Mahaveer Singh Naruka[2], Gaurav Tewari[3*]
[1]Research Scholar,Dept. of ECE
Maharishi University of Information Technology
Lucknow,India
uppal.ashi@gmail.com
[2]Research Supervisor, Dept of ECE
Maharishi University of Information Technology
Lucknow , India
[3*]Corresponding Author
Faculty, Dept of ECE
School of Information and Communication Technology
Gautam Buddha University
Gr. Noida, India
gauravtewari.gbu@gmail.com

Abstract— Generally, it has been observed that due to lack of proper knowledge of disease intensity, the farmer is not able to use the pesticide in proper quantity to treat the diseases. The use of pesticide mostly becomes more than necessary, due to which there is not only a loss of money, but also it causes soil and environmental pollution. If diseases severity-wise labelled data sets are available, it can be used to develop pesticide recommendation systems. Images with least infection severity can be used to train and validate a DL model to capture the plant diseases at very initial stage. Classification techniques may be viewed as variations of detection systems; however, instead of attempting to identify only one particular illness among several diseases, classification methods detect and name the diseases harming the plant. This presents various classification and plant disease detection methods based on image processing with results.

Keywords-Classification Model,Plant Diseases,Image Processing.

I. Introduction

Plant illnesses are a crucial issue in farming that reduces the eminence and quantity of the plant yields. The detection and classification models are a typical strategy applied in farming to diagnose the crop diseases. Disease recognition is a process of determining whether a specific disease present in the plant or not. Image processing techniques are frequently used to detect illness and also to estimate its severity. Usually, classification techniques follow a segmentation and features extraction unit. The segmentation process identifies interested area in the input sample and the feature extraction technique obtains relevant features from the segmented image. In plant disease detection and classification system, generally images of leaf or stem, or fruit are acquired from the plant and use as input image for the disease detection system. These extracted features are then fed into some form of classifier. We have done a deep survey on plant disease recognition and classification systems. Different systems used different approaches. We have organized these approaches as shown in Figure 1.

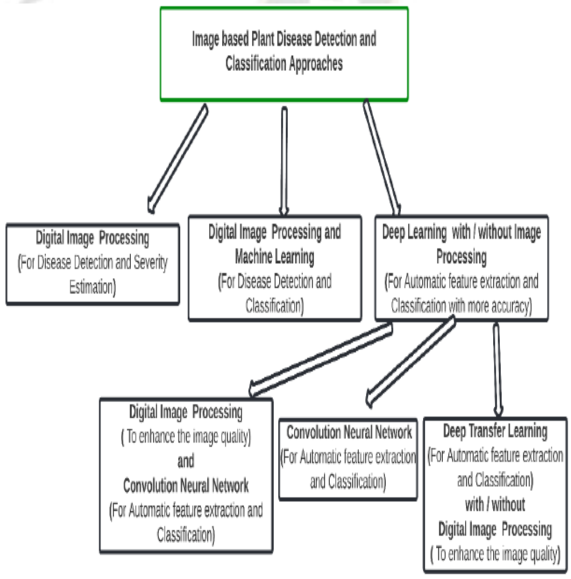

Figure 1. Plant disease recognition approaches based on leaf images

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These approaches can be classified in 5 parts.
1) DIP (To recognize the diseases and to estimate the disease severity)
2) DIP with ML approach (To classify and recognize the diseases)
3) Deep CNN (To classify the diseases by automatically extracting the features)
4) DIP (To enhance the image quality) and Convolution Neural Network (To classify the diseases by automatically extracting the features)
5) Deep Transfer Learning (For Automatic feature extraction and Classification) with / without Digital Image Processing (To improve the image visual characteristics)

We have arranged and discussed these approaches in 4 broad categories in following subsections A, B ,C and D. We have combined 3rd and 4th approaches in one category named as “Automatic feature extraction and classification with Deep learning”. First approach is discussed in subsection A under topic “plant disease detection using image processing”. Second approach is discussed in subsection B under “Disease Detection and classification using image processing and machine learning”. 3rd and 4th techniques are discussed in subsection C under “Automatic feature extraction and classification with Deep learning (Convolution Neural Network)”. Furthermore, fifth approach is illustrated in subsection D under “Use of transfer learning for efficient and effective disease detection and classification result”.

A. Detection of Plant Diseases using Image Processing

Researchers leverage spectroscopy and image processing techniques to remove the problems associated with manual plant disease detection methods. In our study, we explore contribution of image-processing techniques in domain of plant-disease- detection. We have not covered spectroscopy technique here. In this section, plant disease detection and/or severity estimation process using digital image processing is discussed. The fundamental steps required for “disease detection” using DIP is shown in Figure 2.
The process of detecting plant diseases using DIP techniques is divided into the following steps:
1) Image capture: This is very first step in DIP technique. In this process, relevant image (s) is/are collected either directly from crop fields or from well-known datasets. Generally, images of roots, or stems, or branches, or leaves, or fruits are captured from interested plant. In our research, we have utilized leaves images of the plant to conduct the experiments.
2) Image pre-processing: This step is required to get quality images for further processing. In this process visual appearance and characteristics are improved using several image-processing operations. The resizing operation is used to speed up the image processing computation by reducing the size of images. Contrast stretching operation (CLAHE, LAHE etc.) can be used to improve visual appearance of images. Similarly, back ground removal procedures can be carried out to get interested object from input image [1]. Image transformation may be rotation, scaling, translation, and reflection of images. Any image transformation operation can be used as per research requirement. Many more such image processing operations are available, that may be used as image pre-processing operation.

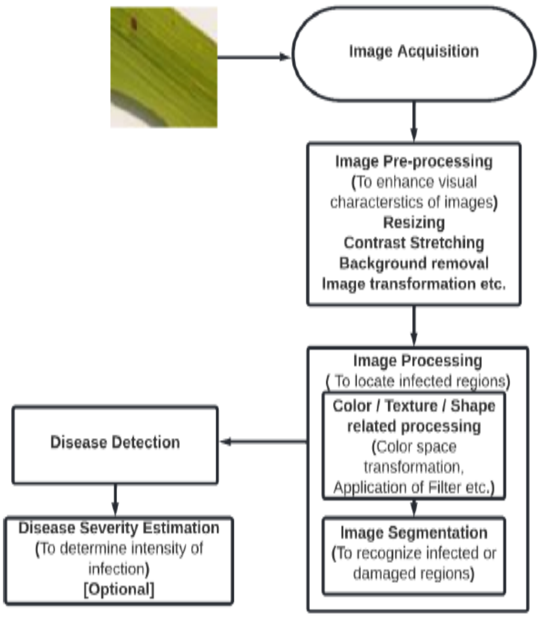

Figure 2. Fundamental steps required for disease detection using DIP

3) Image Processing: These are main computations performed on images to solve the research problems. These operations are applied on pre-processed images to get better results. Color, texture and morphological characteristics of images are analysed in this module. Image segmentation is applied to check abnormality in leaf, stem or fruit images. These image segmentation techniques are based on color/shape/texture.
4) Disease detection and/or Severity Estimation: Once infected regions are located successfully in leaf or fruit using segmentation technique, then disease severity is computed by computing area of infected regions.

B. Disease Recognition and Classification using DIP and ML together

Image processing approaches are intended to enhance agricultural productivity by aiding in agricultural field

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monitoring. Computer vision, in conjunction with soft computing/ML techniques, has been used in various plant pathology studies ("Sabrol and Kumar 2015; Singh et al. 2015a, b") [2,3,4]. The process of detecting crop illnesses using DIP and ML techniques is divided into the following modules: picture capture, image pre-processing, image segmentation, feature extraction, and identification or classification. A fundamental diagram of this approach is depicted in Figure 3.

Adequate training of a classification model on acquired images is needed for accurate identification; First of all, images of interesting parts like stems, roots, leaves, and fruits are acquired from the plants. After image acquisition, numerous pre-processing operations such as smoothening, rotation, scaling, contrast stretching, transformation, etc., are utilized on acquired input images as needed to get cleaned and quality images. Segmentation is then implemented to achieve the regions of interest from the diseased part of plants (leaves/stems/fruits images). Furthermore, the characterising attributes are obtained from the infected region and these features are utilised to provide the training to the classification model. Classification model is designed using ML methods ("SVM, decision tree, Naïve bayes classifier, ANN, etc").

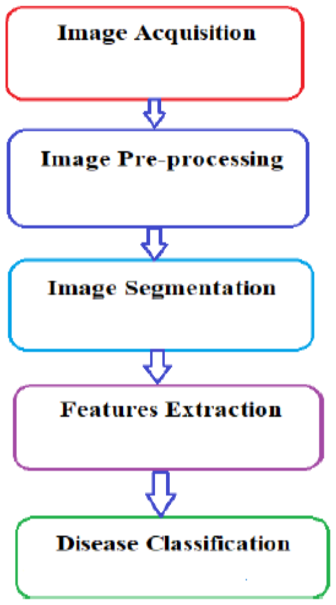

Figure 3 Fundamental steps of plant disease classification using ML techniques [1]

During the validation step, the trained model determines whether the illness seen in the test picture is healthy or infected. Prior to this, the test pictures pass through all of the same stages as the train pictures to achieve significant characteristics from test images.

C. Classification by Automatically extracting the features with Deep learning (CNN)

In the fields of "image-processing and computer-vision", the attention has recently shifted to deep learning (DL) ("Szegedy et al. 2015, LeCun et al., 2015; Cruz et al. 2017") [5,6,7]. DL has demonstrated impressive performances in fields including object recognition, object identification [8], biological picture categorization [9,10], and speech recognition [11]. To use deep neural network capabilities to detect and classify crop diseases, the CNN model has been used most frequently. CNN is capable of performing both tasks feature extraction and classification in one unit. Deep learning is a new technique for extracting features from leaf photos automatically. Convolution neural network (CNN) has been a growing topic for picture categorization due to its ability to extract features automatically. It is able to tackle large data without the need for picture pre-processing. A systematic approach of "plant disease detection and classification" using Deep CNN is depicted in Figure 4.

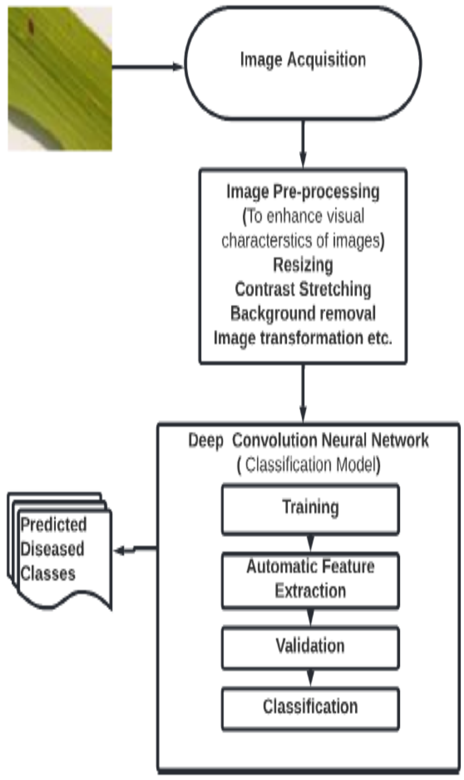

Figure 4. Plant disease detection and classification using Deep CNN

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The initial stage in every DIP program is image-acquisition. The goal of image capture is to acquire pictures of the plant's sick parts. The photos are obtained either from a benchmarked dataset or directly from the agricultural field in this stage. The photographs collected are used as a train and test datasets. Image pre-processing is optional, but many researchers have used DIP concepts to improve the image quality for better classification results [1]. To sanitize the dataset, image preprocessing is performed. Image preprocessing entails a variety of activities that are carried out according to the study requirements. Finally, the CNN model is developed to extract the most relevant features map and to characterize the plant diseases.

D. Use of transfer learning for efficient and effective disease detection and classification result

For the categorization of images, recently, many researchers attract towards transfer learning technique due to its ability to learn the relevant features correctly from the small available data set. Agriculture sector has also not remained untouched by it. Transfer learning not only saves the time of learning, but also gives promising classification accuracy in the fields of image recognition and classification.

The fundamental benefit of adopting TL is that, rather than beginning the learning from fresh, the model utilized the learned patterns of already solved tasks while tackling a similar nature task. As a result, the classifier may make use of prior knowledge rather than having to start from zero. Transfer learning is commonly used in image classification by the application of pre-trained networks. A pre-trained model is one that has been trained on a big dataset. These pre-trained networks with the concept of transfer learning are used to tackle a problem that is comparable to the one, that has already been solved. Most frequently used pre-trained models are mobile net, VGG, Inception v3, DenseNet169, Squeeze net, ResNet50, InceptionResNet v1, InceptionResNet v2, Googlenet,etc. Generally, deep CNN architectures are pre-trained on a large Imagenet dataset [6] before applying transfer learning. Learned weights and biases of pretrained network are utilized to design a DL model for a specific task (disease detection with specific image samples). Final few layers of the pre-trained classifier are modified to make it compatible for the specific task. Finally fine tuning is performed to tune the training parameters for disease classification. A “systematic approach of plant disease detection and classification” using transfer learning is shown in Figure 5.

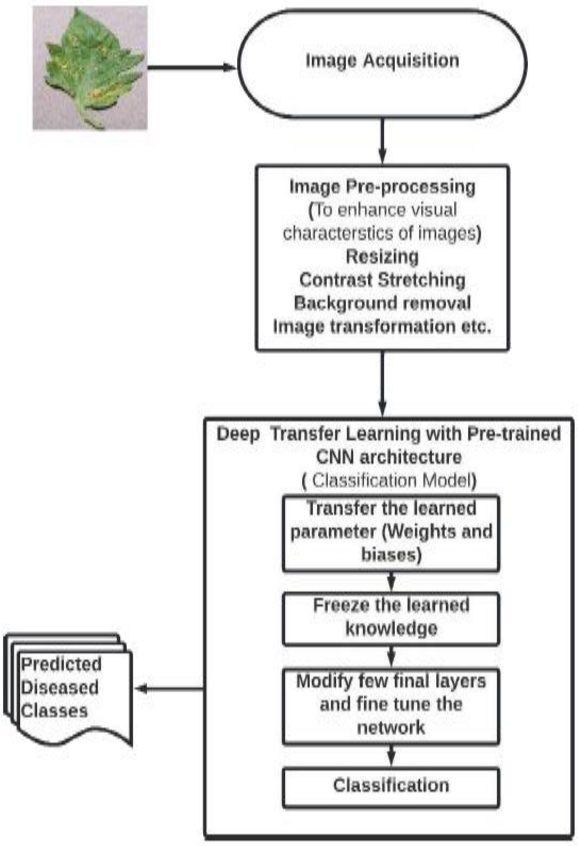

Figure 5. Plant illness recognition and classification using TL

II. CONCLUSION

We have explored whether a simple fully connected Convolution Neural Network architecture can be designed and utilized to recognize and classify the rice plant illnesses effectively by using images of plant leaf, and whether a background removal technique can be utilised to increase the performance even more. For exploration, we have developed a simple fully connected CNN for rice illness(pathogen) recognition and classification using leaf images. Number of filters and size of filters in convolution operation are designed in such a good manner that it outperformed the existing methods with an accuracy of 99.1%. We have used large dataset to overcome the problem of overfitting.

To boost performance even more, we have applied background removal technique on input images before feeding it into suggested FCNN. Here, background removal technique is implemented using Otsu’s global thresholding method. Removal of background from input leaf images, further enhance the classification accuracy with a margin of 0.6%. This way, we have achieved second research objective.

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III. FUTURE SCOPE

We are primarily focusing on 2 crops diseases namely; paddy diseases and tomato diseases. This work can be extended to cover more crop diseases. This work mainly focuses on leaf of plant to diagnose the plant diseases. Future work could focus on extending the suggested work to diagnose the plant diseases using stems, fruits, and flowers. The approach assume that one leaf is infected by only one disease. This work can be extended to diagnose the multiple diseases in a single leaf. This work can be applied on real field dataset collected directly from crop fields by IoT system. This study may be extended to include the development of a mobile application for the proposed technique to automatically recognise and monitor a variety of crop diseases using smartphones and tablets.

REFERENCES

[1]. Upadhyay, S.K., Kumar, A. (2022). A novel approach for rice plant diseases classification with deep convolutional neural network. International Journal of Information Technology 14, pp.185–199 (2022). https://doi.org/10.1007/s41870-021-00817-5

[2]. Sabrol, H., Kumar, S. (2015). Recent studies of image and soft computing techniques for plant disease recognition and classifcation. International Journal of Computer Application 126(1): pp. 44–55. https://doi.org/10.5120/ijca2 015905982

[3]. Singh, V., Gupta, S., Saini, S. (2015a). A methodological survey of image segmentation using soft computing techniques. In: Conference proceeding— 2015 international conference on advances in computer engineering and applications, ICACEA 2015, pp 419–422. https://doi.org/10.1109/ICACEA.2015.7164741

[4]. Singh, V., Varsha, Misra, A.K. (2015b). Detection of unhealthy region of plant leaves using image processing and genetic algorithm. In: Conference proceeding—2015 International conference on advances in computer engineering and applications, ICACEA 2015, pp 1028–1032. https://doi.org/10.1109/ICACE A.2015.7164858

[5]. Szegedy, C., Liu, W., Jia, Y., Sermanet, P., Reed, S., Anguelov, D., Arbor, A., 2015. Going deeper with convolutions. In: 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). Boston, MA, USA, pp. 1– 9.

[6]. LeCun, Y., Bengio, Y., Hinton, G., (2015). Deep learning. Nature 521, 436– 444

[7]. Cruz AC, Luvisi A, De Bellis L and Ampatzidis Y (2017). X-FIDO: An Effective Application for Detecting Olive Quick Decline Syndrome with Deep Learning and Data Fusion. Frontiers in Plant Science 8:1741.doi: 10.3389/fpls.2017.01741

[8]. Redmon, J., Divvala, S., Girshick, R., and Farhadi, A. (2016). You only look once: Unified, real-time object detection. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 779-788).

[9]. Gour, M., Jain, S. (2020). Stacked convolutional neural network for diagnosis of covid-19 disease from x-ray images. arXiv preprint arXiv:2006.13817.

[10]. Gour, M., Jain, S., and Kumar, T. S. (2020). Residual learning-based CNN for breast cancer histopathological image classification. International Journal of Imaging Systems and Technology, 30(3), pp.621-635.

[11]. Abdel-Hamid, O., Mohamed, A.R., Jiang, H., Deng, L., Penn, G., Yu, D. (2014). Convolutional neural networks for speech recognition. IEEE/ACM Trans. Audio, Speech, Language Process. 22 (10), 1533–1545.

[12]. Russakovsky, O., Deng, J., Su, H., Krause, J., Satheesh, S., Ma, S. et al. (2015). Imagenet large scale visual recognition challenge. International Journal of Computer Vision 115: 211–252.