



## Plant Leaf Disease Detection – A Machine Learning Approach

Sejal Pate<sup>1</sup>, Sujit Sable<sup>2</sup>, Rohit Jadhav<sup>3</sup>, Poonam Badadhe<sup>4</sup>, Chandrashekhar Patil<sup>5</sup>

Department of E&TC, SKNCOE, SPPU, Pune

<sup>1</sup>sejalpate0903@gmail.com, <sup>2</sup>sujitsable1@gmail.com, <sup>3</sup>rohitjadhav45.skncoe.entc@gmail.com,

<sup>4</sup>poonam.badadhe\_skncoe@sinhgad.edu, <sup>5</sup>[chandrashekhar.patil\\_skncoe@sinhgadl.edu](mailto:chandrashekhar.patil_skncoe@sinhgadl.edu)

**Abstract --** Agriculture proves to be major source of income for many farmers in our country. According to survey conducted in 2021 58% of population depends on agriculture. Besides, many farmers are cultivating in remote areas of the world with the lack of accurate knowledge and disease detection, however, they rely on manual observation on grains and vegetables, as a result, they are suffering from a great loss. For overcoming such issues there is need to demonstrate a practice where farmers can easily detect plant leaf diseases in early stages. Since, for addressing such issues digital farming practices can be involved where use of machine learning algorithm can be used. Eventually, along with detected disease remedy can also be insisted.

**Keywords –** Agriculture, Vegetables, Farmers, Disease, Detection, Machine Learning.

### I. INTRODUCTION

Plants nowadays are affected by many diseases. They cause economic, social and ecological losses and many more. Image processing involves steps like image pre- processing, segmentation, feature extraction and classification. Agro-scientist can provide a better solution by using the images and videos of crops that provides a better view. Many of the farmers are not able to identify the diseases in the plants which may lead to loss in agriculture products. Plants are very essential in our life as they provide source of energy and overcome the issue of global warming. To make things easier image processing is used, that helps to overcome these kinds of situations, by extracting the features of the leaves where the diseases can be easily detected. Plant diseases can be extensively grouped by the idea of their essential causal operator, either irresistible or non-infectious. Agriculture has become the key to rise in human civilization it is the art and science of cultivating live stocks and plants. There are many diseases that affect the plants, where the symptoms are not recognizable at the very first stage which may lead to social and economic losses. Hence, it is most important to identify plants disease in an accurate and timely way. The Convolutional Neural Network (CNN) resulted in improved accuracy of recognition.

### II.

### III. LITERATURE REVIEW

In 2015, S. Khirade tackled the problem of plant disease detection using digital image processing techniques and back propagation neural network (BPNN) [1]. Authors have elaborated different techniques for the detection of plant disease using the images of leaves. They have implemented Otsu's thresholding followed by boundary detection and spot detection algorithm to segment the infected part in leaf. After that they have extracted the features such as color, texture, morphology, edges etc. for classification of plant disease. BPNN is used for classification i.e., to detect the plant disease.

Shiroop Madiwalar and Medha Wyawahare analyzed different image processing approaches for plant disease detection in their research [2]. Authors analyzed the color and texture features for the detection of plant disease. They have experimented their algorithms on the dataset of 110 RGB images. The features extracted for classification were mean and standard deviation of RGB and YCbCr channels, grey level co- occurrence matrix (GLCM) features, the mean and standard deviation of the image convolved with Gabor filter. Support vector machine classifier was used for classification. Authors concluded that GCLM features are

effective to detect normal leaves. Whereas color features and Gabor filter features are considered as best for detecting anthracnose affected leaves and leaf spot respectively. They have achieved highest accuracy of 83.34% using all the extracted features.

Peyman Moghadam et Al. demonstrated the application of hyperspectral imaging in plant disease detection task [3]. visible and near-infrared (VNIR) and short-wave infrared (SWIR) spectrums were used in this research. Authors have used k-means clustering algorithm in spectral domain for the segmentation of leaf. They have proposed a novel grid removal algorithm to remove the grid from hyperspectral images. Authors have achieved the accuracy of 83% with vegetation indices in VNIR spectral range and 93% accuracy with full spectrum. Though the proposed method achieved higher accuracy, it requires the hyperspectral camera with 324 spectral bands so the solution becomes too costly.

Sharath D. M. et Al. developed the Bacterial Blight detection system for Pomegranate plant by using features such as color, mean, homogeneity, SD, variance, correlation, entropy, edges etc. Authors have implemented grab cut segmentation for segmenting the region of interest in the image [4]. Canny edge detector was used to extract the edges from the images. Authors have successfully developed a system which can predict the infection level in the fruit.

Garima Shrestha et Al. deployed the convolutional neural network to detect the plant disease [5]. Authors have successfully classified 12 plant diseases with 88.80% accuracy. The dataset of 3000 high resolution RGB images were used for experimentation. The network has 3 blocks of convolution and pooling layers. This makes the network computationally expensive. Also, the F1 score of the model is 0.12 which is very low because of higher number of false negative predictions.

#### IV. METHODOLOGY

The convolution layer has extracted some valuable features from the data. These features are sent to the fully connected layer that generates the final results. The fully connected layer in a CNN is nothing but the traditional neural network!

The output from the convolution layer was a 2D matrix. Ideally, we would want each row to represent a single input image. In fact, the fully connected layer can only work with 1D data. Hence, the values generated from the previous operation are first converted into a 1D format.

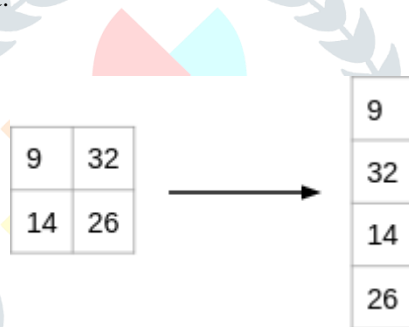


Fig.1 2 D to 1D format

Once the data is converted into a 1D array, it is sent to the fully connected layer. All of these individual values are treated as separate features that represent the image. The fully connected layer performs two operations on the incoming data – a linear transformation and a non- linear transformation.

We first perform a linear transformation on this data. The equation for linear transformation is:

$$Z = WT.X + b \dots\dots\dots(1).$$

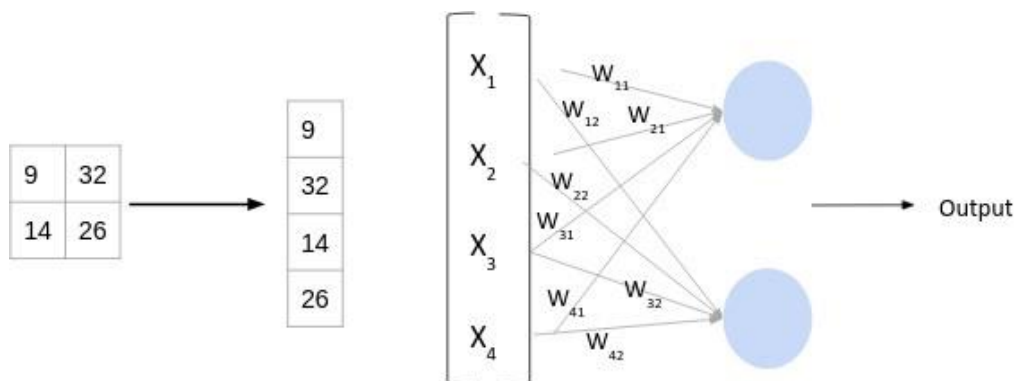


Fig.2 Fully connected layers of CNN

Here,  $X$  is the input,  $W$  is weight, and  $b$  (called bias) is a constant. Note that the  $W$  in this case will be a matrix of (randomly initialized) numbers

Consider the case where there are  $K$  anchor vectors in the  $N$ -dimensional unit sphere, denoted by  $a_k$ ,  $k = 1, \dots, K$ . For given  $x$ , its  $K$  rectified correlations with  $a_k$ ,  $k = 1, \dots, K$ , defines a nonlinear transformation from  $x$  to an output vector

$$y = (y_1, \dots, y_k, \dots, y_K)^T, \quad (2)$$

Where,

$$y_k(x, a_k) = \max(0, a_k^T x) \equiv \text{Rec}(a_k^T x). \quad (3)$$

The form in Eq. (2) is ReLU. Other variants such as the sigmoid function and the leaky ReLU are acceptable. As long as the negative correlation values remain to be small, these vectors are weakly correlated and they will not have a major impact on the final result.

$$S_\mu = \left\{ x \mid \|x - \mu\| = \left[ \sum_{n=1}^N (x_n - \mu)^2 \right]^{1/2} = 1 \right\}. \quad (4)$$



Fig. 3: Some samples from the dataset are shown

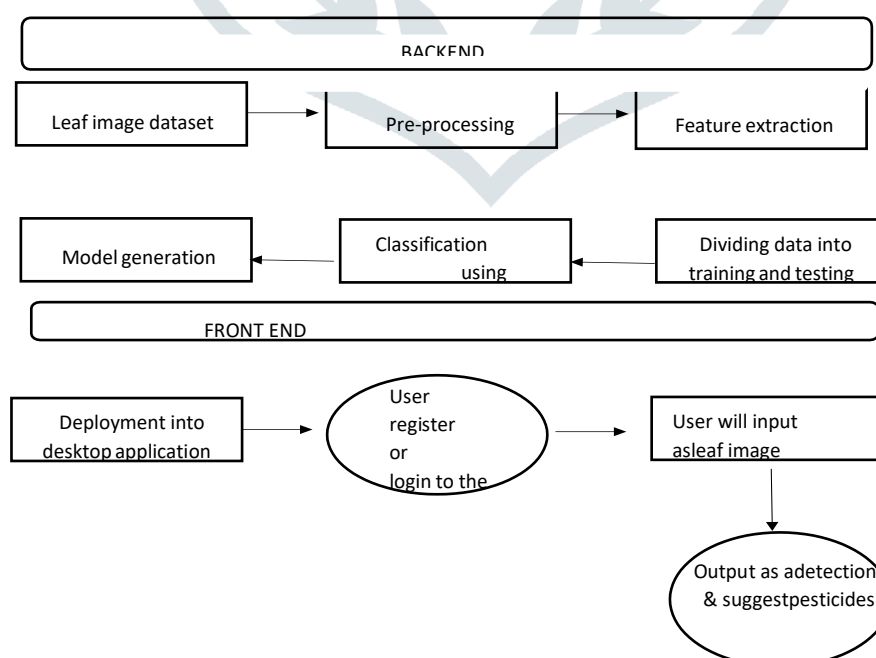


Fig. 4: Block Diagram: Overview of working of System

## V. RESULT AND DISCUSSION

The average accuracy for detecting plant leaf disease is 70%.

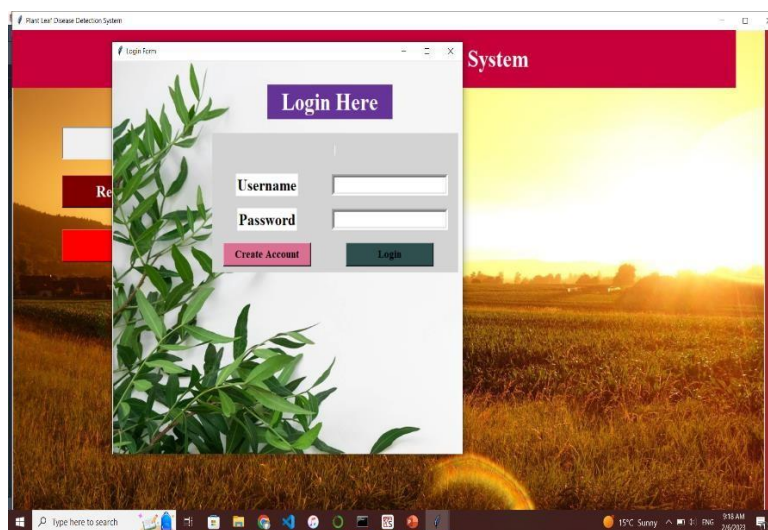


Fig. 5: -Login Page-



Fig. 6: -Registration Page-



Fig. 7: -Home Page- (After user Login)



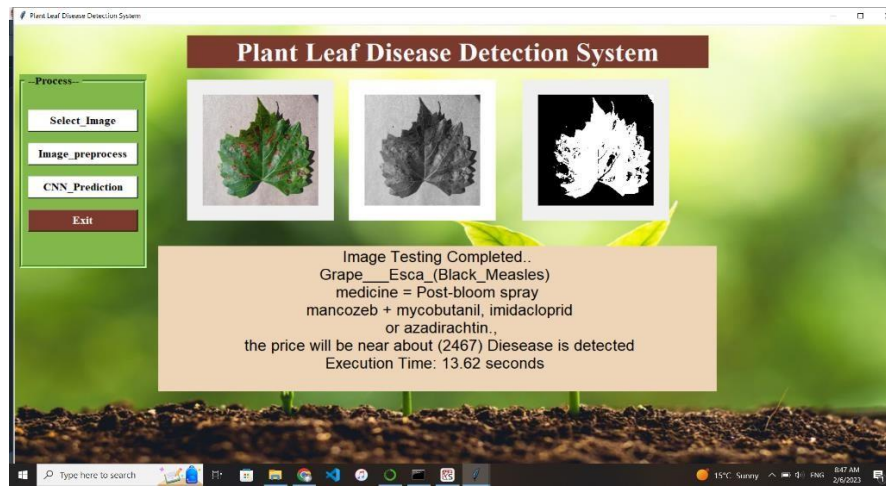


Fig. 8: -Pre-processing and Final Output-

## VI. CONCLUSION

The proposed system is computationally efficient because of the use of image processing and machine learning model. We have successfully developed a computer vision-based system for plant disease detection with average 90% accuracy. It is observed from Table 1 that, our technique is accurate and efficient as compared to other systems. Also, this system does not require hardware which makes it more cost-effective solution as well.

Table 1: Comparison of Systems

Author	S. Khirade (2015)	Shiroop Madiwala (2017)	Peyman Moghadam (2017)	Sharath D.M. (2019)	Garima Shrestha (2020)	Proposed Method
Algorithm	Digital image processing & BPNN	Digital image processing & SVM	Hyperspectral imaging & SVM	Digital image processing	CNN	ML & Digital image processing
Accuracy	-	83%	93%	-	88%	90%
Computationally Efficient	✗	✓	✗	✓	✗	✓
Hardware Requirement	✗	✗	✓	✗	✗	✗

## REFERENCES

- [1] R. Kundu, U. Chauhan and S. P. S. Chauhan, "Plant Leaf Disease Detection using ImageProcessing," 2022 2nd International Conference on Innovative Practices in Technology and Management (ICIPTM), 2022, pp. 393-396, doi: 10.1109/ICIPTM54933.2022.9754170.
- [2] Miaomiao Ji, Lei Zhang, Qiufeng Wu," Automatic Grape Leaf Diseases Identification via United Model Based on Multiple Convolutional Neural Networks", Elsevier, Volume 7, Issue 3, September 2022, Page 418-426
- [3] JUN SUN, YU YANG, XIAO FEI HE, AND XIAO HONG WU, "Northern Maize Leaf Blight Detection under Complex Field Environment Based on Deep Learning", IEEE, 2021, Volume: 8 Page(s): 33679 – 3368.
- [4] MohitAgarwalaAbhishekSinghb SiddharthaArjariacAmitSi nhad SuneetGuptaa," To LeD: Tomato Leaf Disease Detection using Convolution Neural Network", Elsevier, 2020, Volume 167, 2020, Pages293-301.
- [5] Junde Chena, Jinxiu Chena, Defu Zhanga, Yuandong Sunb, Y.A. Nanekarana," Using deep transferlearning for image-based plant disease identification", Elsevier, June 2020, Volume 173, June 2020, 105393

