# CONJECTURE OF CROP ADVANCEMENT STAGES USING NEURAL NETWORKS

# Jasmin Pemeena Priyadarshini M<sup>1</sup>, Aastha Agarwal<sup>2</sup>, Shagun Rai<sup>3</sup>, Prateek Agarwal<sup>4</sup>

School of Electronics Engineering, Vellore Institute of Technology, Vellore, India<sup>1</sup>

----- ABSTRACT ----

This paper proposes that deep learning is a branch of artificial intelligence. In recent years, the advantages of automatic learning and feature extraction have been a wide concern in academic and industrial circles. It has been widely used in image and video processing, voice processing, and natural language processing. At the same time, it has also become a research hotspot in the field of agricultural plant protection, such as plant disease recognition and pest range assessment, etc. The application of deep learning in plant disease recognition can avoid the disadvantages caused by artificial selection of disease spot features, make plant disease feature extraction more objective, and improve the research efficiency and technology transformation speed. This review provides the research progress of deep learning technology in the field of crop leaf disease identification in recent years. In this paper, we present the current trends and challenges in the detection of plant leaf disease using deep learning and advanced imaging techniques. We used the Convolutional Neural Network (CNN). Accuracies ranging from 95% - 100% were obtained.

KEYWORDS - Accuracy, CNN, Leaf disease, MATLAB, Pre-processing, Segmentation,

# I. INTRODUCTION

Modern technologies have allowed human civilization to provide enough food for more than 7 billion people worldwide. However, food security remains a fundamental issue affecting several factors, such as climate change, plant diseases, biotic stress, and others. Plant diseases threaten global food security and create repercussions for small farmers, whose livelihoods depend on healthy crops. More than 80% of agricultural production is produced by smallholder farmers, and at the same time, more than 50% of loss is seen due to pests and diseases. Consistent efforts are made to prevent crop loss by consulting many domain experts to support agriculture extension organizations and other institutions. It is a costly, labor-intensive, and time-consuming process. On the other hand, in many countries, in rural areas, farmers may not have an idea to contact experts due to a lack of facilities. Early detection of plant diseases (before symptoms begin) may be a valuable source of knowledge for implementing effective disease control measures to prevent plant disease spread. Many computer vision-based deep learning applications have recently been deployed for agriculture tasks, such as pest prediction, plant disease detection, water resource management, etc. Such an autonomous system can help the farmers and agronomists to make the decisions in time and reduce significant economic loss. In this paper, we propose a real-time solution for automated plant

disease detection by exploiting EfficientDet as the deep learning framework.

We present the current trends and challenges for the detection of plant leaf disease using deep learning and advanced imaging techniques.

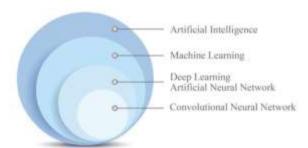


Figure 3.1

#### II. EXISTING METHOD

Plant diseases have a detrimental effect on the health of food production in agriculture. As a consequence, it significantly decreases the quality, quantity, and productivity of the yield. Thus, for sustainable agriculture, automated detection and diagnosis of plant diseases at an early stage of growth are highly desired. While several computer vision-based applications have been suggested for this process, they still suffer from long-lasting training/testing time with large datasets. Besides, due to the hardware limitation and computational complexity, such model development is crucial in handheld devices. This research presents a new transfer learning-based



optimized EfficientDet deep learning framework as a practical solution for automated plant disease detection. A total of 3,038 images are collected from two public dataset repositories and annotated manually to train the model. The proposed model performance is evaluated in terms of mean Average Precision (mAP). It achieves an overall mean average precision. Of 74.10% with a substantially fewer number of parameters and FLOPs than other state-of-the-art approaches. Such a framework can be implemented on devices with minimal computing resources to make reliable and timely decisions. This process comes under deep learning. The deep learning technique needs more cost to finish the project when compared to CNN techniques

#### III. PROPOSED METHOD

The proposed technique of this project is that the occurrence of plant diseases has a negative impact on agricultural production. If plant diseases are not discovered in time, food insecurity will increase. Early detection is the basis for effective prevention and control of plant diseases, and they play a vital role in the management and decisionmaking of agricultural production. In recent years, plant disease identification has been a crucial issue. Disease-infected plants usually show obvious marks or lesions on leaves, stems, flowers, or fruits. Generally, each disease or pest condition presents a unique visible pattern that can be used to uniquely diagnose abnormalities. Usually, the leaves of plants are the primary source for identifying plant diseases, and most of the symptoms of diseases may begin to appear on the leaves. Here the segmentation process is more accurately done. Because segmentation of leaf areas leads to an accurate classification. This process comes under deep learning convolutional neural networks.

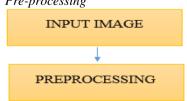
# IV. METHODOLOGY

A. Input

## INPUT IMAGE

Here, giving the collected dataset as input from the system.

B. Pre-processing



The aim of pre-processing is an improvement of the image data that suppresses undesired distortions or enhances some image features relevant for further processing and analysis tasks.

There are 4 different types of Image Pre-Processing techniques and they are listed below.

- Pixel brightness transformations/ Brightness corrections.
- Geometric Transformations.
- Image Filtering and Segmentation.
- Fourier transform and Image re-saturation.

#### C. Segmenttion

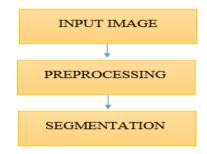
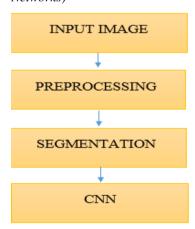


Image segmentation is a method in which a digital image is broken down into various subgroups called Image segments which helps in reducing the complexity of the image to make further processing or analysis of the image simpler. Segmentation in easy words is assigning labels to pixels. All picture elements or pixels belonging to the same category have a common label assigned to them. For example: Let's take a problem where the picture has to be provided as input for object detection. Rather than processing the whole image, the detector can be inputted with a region selected by a segmentation algorithm. This will prevent the detector from processing the whole image thereby reducing inference time.

# D. CNN Algorithm (----Convolutional Neural Networks)



It is assumed that the reader knows the concept of Neural networks. When it comes to Machine Learning, Artificial Neural Networks perform really well. Artificial Neural Networks are used in various classification tasks like images, audio, and words. Different types of Neural Networks are used for different purposes, for example for predicting the



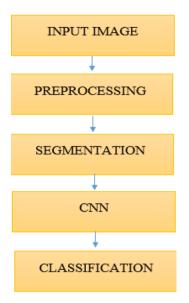
sequence of words we use Recurrent Neural Networks more precisely an LSTM, similarly for image classification we use Convolution Neural networks. In this blog, we are going to build a basic building block for CNN. Before diving into the Convolution Neural Network, let us first revisit some concepts of Neural networks. In a regular Neural Network, there are three types of layers:

- 1. Input Layers: It's the layer in which we give input to our model. The number of neurons in this layer is equal to the total number of features in our data (number of pixels in the case of an image).
- 2. Hidden Layer: The input from the Input layer is then fed into the hidden layer. There can be many hidden layers depending upon our model and data size. Each hidden layer can have different numbers of neurons which are generally greater than the number of features. The output from each layer is computed by matrix multiplication of output of the previous layer with learnable weights of that layer and then by the addition of learnable biases followed by activation function which makes the network nonlinear.
- **3. Output Layer:** The output from the hidden layer is then fed into a logistic function like sigmoid or SoftMax which converts the output of each class into the probability score of each class.

The data is then fed into the model and output from each layer is obtained. This step is called feedforward, we then calculate the error using an error function, some common error functions are cross-entropy, square loss error, etc. After that, we backpropagate into the model by calculating the derivatives. This step is called Backpropagation which basically is used to minimize the loss. Here's the basic python code for a neural network with random inputs and two hidden layers.

# E. Classification

Classification methods aim at identifying the category of a new observation among a set of categories on the basis of a labeled training set. Depending on the task, anatomical structure, tissue preparation, and features the classification accuracy varies.



#### V. SOFTWARE SYSTEM AND DESIGN

MATLAB (matrix laboratory) is a numerical computing environment and fourth-generation programming language. Developed by MathWorks, MATLAB allows matrix manipulations, plotting of functions and data, implementation of algorithms, creation of user interfaces, and interfacing with programs written in other languages, including C, C++, Java, and Fortran. MATLAB is used in a vast area, signal and image including processing, communications, control design, test and measurement, financial modeling and analysis, and computational. Add-on toolboxes (collections of special-purpose MATLAB functions) extend the **MATLAB** environment to solve particular classes of problems in these application areas.

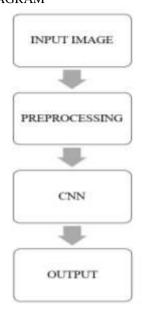
#### **Features of MATLAB**

- High-level language for technical computing.
- Development environment for managing code, files, and data.
- Interactive tools for iterative exploration, design, and problem-solving.



#### SYSTEM DESIGN

#### **BLOCK DIAGRAM**

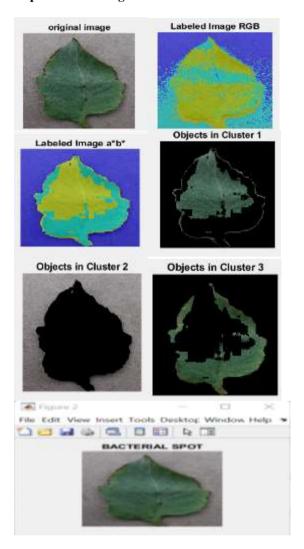


#### VI. PERFORMANCE ANALYSIS

In general, a plant becomes diseased when it is continuously disturbed by some causal agent that results in an abnormal physiological process that disrupts the plant's normal structure, growth, function, or other activities. This interference with one or more of a plant's essential physiological or biochemical systems elicits characteristic pathological conditions or symptoms. Plant diseases can be broadly classified according to the nature of their primary causal agent, either infectious or noninfectious. Infectious plant diseases are caused by a pathogenic organism such as a fungus, bacterium, mycoplasma, virus, viroid, nematode, or parasitic flowering plant. An infectious agent is capable of reproducing within or on its host and spreading from one susceptible host to another. Non-infectious plant diseases are caused by unfavourable growing conditions, including extremes of temperature, disadvantageous relationships between moisture and oxygen, toxic substances in the soil or atmosphere, and an excess or deficiency of an essential mineral. Because noninfectious causal agents are not organisms capable of reproducing within a host, they are not transmissible. In nature, plants may be affected by more than one disease-causing agent at a time. A plant that must contend with a nutrient deficiency or an imbalance between soil moisture and oxygen is often more susceptible to infection by a pathogen, and a plant infected by one pathogen is often prone to invasion by secondary pathogens. The combination of all disease-causing agents that affect a plant makes up the disease complex. Knowledge of normal growth habits, varietal

characteristics, and the normal variability of plants within a species—as these relate to the conditions under which the plants are growing—is required for a disease to be recognized.

## **Experimental Images**

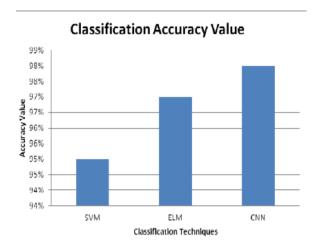


## VII. ACCURACY COMPARISON

Crop	Disease	Classification	Accuracy	
Detection	Detection Methods			
	22.04	50-200	ē.	
SVM		95%		
EI	ELM		97%	
Cl	CNN		98%	
(E				

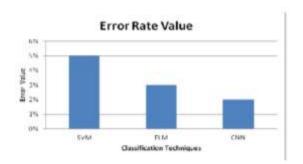
**Table 2.1 Classification Accuracy Value** 





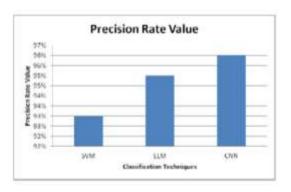
Crop Disease	Error Rate Value
Detection Methods	
SVM	5%
ELM	3%
CNN	2%

**Table 3.2 Error Rate Value** 



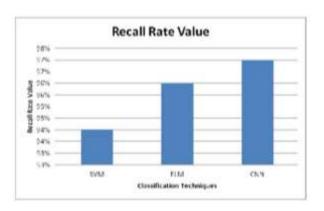
Precision Rate Value	
93%	
95%	
96%	

**Table 3.3 Precision Rate Value** 



Crop Disease	Recall Rate Value	
Detection Methods		
SVM	94%	
ELM	96%	
CNN	97%	

**Table 3.4 Recall Rate Value** 



# VIII. APPLICATIONS AND SCOPE FOR FUTURE IMPROVEMENT

#### **Applications**

- The major applications of the proposed system basically point to automated industrial applications,
- To support easy detection in many Siddha industries also.
- Image segmentation plays an essential role in many image processing applications.
- Low SNR conditions and various artifacts make its automation challenging.
- To achieve robust and accurate segmentation.

#### **Scope For Future Improvements**

In the future, with more time and with more comprehensive research the proposed system can be made more accurate. Also, new plant leaf disease identification algorithms can be added so as to give better results.



### IX. CONCLUSION

A new method is proposed for the classification of plant diseases. The whole method is based on the CNN (Convolutional Neural Network) in deep learning. The diseased area is automatically defined by an algorithm. The CNN algorithm is to detect better accuracy and to get a better output. Our detected contours closely approximate the manually traced ones.

#### X. REFERENCES

- 1. A. P. Tai, M. V. Martin, and C. L. Heald, "Threat to future global food security from climate change and ozone air pollution," Nature Climate Change, vol. 4, no. 9, pp. 817–821, 2014.
- 2. R. N. Strange and P. R. Scott, "Plant disease: a threat to global food security," Annual Review of phytopathology, vol. 43, pp. 83–116, 2005.
- 3. S. Sankaran, A. Mishra, R. Ehsani, and C. Davis, "A review of advanced techniques for detecting plant diseases," Computers and Electronics in Agriculture, vol. 72, no. 1, pp. 1–13, 2010.
- 4. M. A. Rapunzel, E. E. Hassler, R. Rogers, G. Formato, and J. A. Cazier, "Designing a Smart Honey Supply Chain for Sustainable Development," in IEEE Consumer Electronics Magazine, 2021, DOI: 10.1109/MCE.2021.3059955.
- D. Ashourloo, H. Haghighi, A. A. Matkan, M. R. Mobasheri, and A. M. Rad, "An investigation into machine learning regression techniques for the leaf rust disease detection using hyperspectral measurement," IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 9, no. 9, pp. 4344–4351, 2016.
- 6. J. Sekulska-Nalewajko and J. Goclawski, "A semiautomatic method for the discrimination of diseased regions in detached leaf images using fuzzy c-means clustering," in Perspective Technologies and Methods in MEMS Design. IEEE, pp. 172–175, 2011.
- 7. P. K. Tripathy, A. K. Tripathy, A. Agarwal, and S. P. Mohanty, "My Green: An IoT-Enabled Smart Greenhouse for Sustainable Agriculture," in IEEE Consumer Electronics Magazine, 2021, DOI: 10.1109/MCE.2021.3055930.
- 8. Vitas, Dijana, Martina Tomic, and Matko Burul.
  "Traffic Light Detection in Autonomous Driving
  Systems." IEEE Consumer Electronics
  Magazine 9, no. 4 (2020): 90-96.
- 9. S. H. Lee, C. S. Chan, S. J. Mayo, and P. Remagnino, "How deep learning extracts and learns leaf features for the plant classification," Pattern Recognition, vol. 71, pp. 1–13, 2017.
- V. Udutala pally, S. P. Mohanty, V. Pallagani, and V. Khandelwal, "scrap: A novel device for sustainable automatic disease prediction, crop selection, and irrigation in internet-of-agrothings for smart agriculture," IEEE Sensors Journal, 2020, DOI: 10.1109/JSEN.2020.3032438.