RESEARCH ARTICLE OPEN ACCESS

Detection of Plant Leaf Disease Using Deep Learning and Convolutional Neural Networks

Dr. Subba Reddy Borra[1], K. Ruchitha[2], M. Monika[3], M. Navya Satya Sree [4]

1 Professor and Head, Department of Information Technology,
Malla Reddy Engineering College For Women (UGC-Autonomous),
Hyderabad, India
Email: bvsr79@gmail.com

2 Department of Information Technology,
Malla Reddy Engineering College For Women (UGC- Autonomous),
Hyderabad, India
Email : kruchitha2009@gmail.com

3 Department of Information Technology,
Malla Reddy Engineering College For Women (UGC- Autonomous),
Hyderabad, India
Email : monikamasireddy@gmail.com

4 Department of Information Technology,
Malla Reddy Engineering College For Women (UGC- Autonomous),
Hyderabad, India
Email : navyamattaparthi702@gmail.com

Abstract:

When plants and crops are attacked by pests, it affects the country agricultural production. Farmers and professionals usually look at plants with the naked eye to detect and identify diseases. However, this method can be time consuming, expensive and error prone. Automatic detection using image processing technology provides fast and accurate results. This paper describes a novel approach to develop a model for plant disease detection based on leaf image classification using convolutional network. Advancement in computer vision offer opportunities to improve precision crop protection practices and expand the market for computer vision products in the precision agriculture sector. The new training methods and methodology used make it quick and easy to implement the system in practise. All the mandatory steps required to implement this disease detection model are fully explained throughout the document. First, collect images to create an agronomist-rated database and create a deep learning framework to perform deep CNN training. This method paper is a novel approach to plant disease detection using a deep convolutional neural network trained and fine-tuned to accurately fit a database of individually collected plant leaves for various plant diseases.

***Keywords*— Convolutional Neural Networks(CNN), Plant Diseases Detection, Precision agriculture, Deep learning**

I. INTRODUCTION

There're multiple ways to detect plant diseases. Some pathologies might not have symptoms or are felt to work too slowly. Advanced analytics are mandatory in these situations. However, since most diseases cause some symptoms in the visible spectrum, visual inspection by trained professionals is the primary technique used to detect plant diseases in practice. To achieve an accurate diagnosis of plant diseases, plant pathologists must have good observational skills to identify

the characteristic symptoms. Fluctuations in symptoms exhibited by diseased plants can cause erroneous diagnoses. Advances in computer vision present an opportunity to expand and enhance the practice of precise plant protection and extend the market of computer vision applications in the field of precision agriculture. Each junction and unit itself may have a threshold or limiting function such that a signal must cross a boundary before propagating to other neurons.

Backward propagating is the use of forward stimuli to reset the weight of "forward" neural units. This is done sometimes in combination with training with known correct results. More modern networks are somewhat free-flowing in terms of stimulation and inhibition, with connections interacting in much more chaotic and complex ways. Most advanced in that units can be formed dynamically and nullified others. The purpose of neural networks is to solve problems in the same way as the human brain, but some neural networks are more abstract. Modern neural network projects typically operate with thousands to millions of neural units and millions of connections, yet are orders of magnitude less complex than the human brain and approach the computational power of a worm. Thing. New brain research often inspires new patterns in neural networks. A new approach is to use further extending connections that connect layers of processing rather than always being localized to adjacent neurons. Other studies, such as deep learning, which study different kinds of signals propagated by axons over time, involve interpolations that are more complex than simply a set of Boolean variables that are turned on or off. The entry can also be any value between 0 and 1. Neurons also have weights for each input and an overall bias. Weights are real numbers that represent the importance of each input to the output. Bias is used to control how easily the neuron reaches output 1. It is easy for a neuron with a very large bias to output a 1, but if the bias is very negative it is difficult.

II. EXISTING SYSTEM

Since the late 1970s, computer-aided image processing techniques applied to agricultural engineering research have become a popular method. Agricultural research uses machine learning techniques such as artificial neural networks (ANN), decision trees, k-means, k-nearest neighbors, and support vector machines (SVMs). Traditional approaches to image classification tasks have been based on manually constructed features such as SIFT, SURF and used some form of learning algorithm in these features spaces. This makes the performance of all these approaches highly dependent on the underlying predefined characteristics.

III. PROPOSED SYSTEM

Convolutional Neural Networks (CNNs) are supervised deep learning techniques that have shown revolutionary power for a variety of computer vision and image-based applications. Components of a CNN model includes convolutional layers, pooling layers, fully connected layers, and activation functions. The use of these components depends on your network architecture. This model is implemented in the proposed work Convolution Layer. This layer performs a weight matrix (or filter) convolution operation on the input image to produce a stack of filtered images. Filters are multiplied by patches of the image matrix selected at a particular step. Pooling Layer: This pooling layer serves to reduce the number of parameters in the image stack and reduce the amount of computation required. The most common form of pooling is Max Pooling. This selects the maximum value from each small pooling window. Fully Connected Layer: This layer identifies very high-level features that are highly correlated to an object or class. The input to the fully connected plane is the set of features used to classify the image without considering the spatial structure of the image. Most models use two fully glued layers. Flattening is a process for laying out a three Dimensional volume into a one Dimensional vector. Activation Layer: This layer is used to observe the firing rate of neurons.

IV. ADVANTAGES

- This network is used to automatically identify and to stores all features from the trained data set.
- Robust classifications - independent of scale, orientation and occlusion.
- A convolutional network is the use of shared weights in convolutional layers. That is, the same filter (weight bank) is used for each pixel in the layer.

This reduces both memory requirements and performance.

V. MODULES

Acquisition of image datasets:

Datasets were acquired manually using different digital cameras, augmented and segmented as required, and saved in separate folders to identify different diseases of leaves of different plants. images can be distinguished from healthy images. Saved images can be either colour, grayscale, or segmented images. Data sets can be downloaded from opensource websites. The dataset typically used for pre-training in deep learning architecture is ImageNet for object classification. Malaya Key Dataset for Plant Village and Plant Identification for Image Classification

Image Pre-processing:

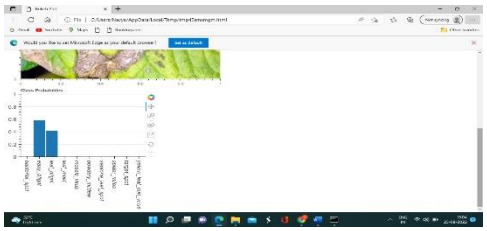
Pre-processing reduces size and crops an image to a specific size or region of interest. It also extends the image to the required colour gamut for processing. Enter the resolution and model size for each architecture by calculating the number of parameters for each layer based on the sum of the products of weights and biases for each layer. The segmented grayscale version of the image offers higher performance compared to RGB image processing. No. The proposed work therefore uses colour images and is scaled to 64 x 64 resolution for further processing.

Feature Extraction: The convolutional layer extracts features from the scaled image. Compared to commonly designed feature extractor such as SIFT, CNN learns different feature map weights and biases for a particular feature extractor. An adjusted nonlinear activation function is applied after convolution. This introduces nonlinearity into the convolutional neural networks. A pooling layer reduces the dimensionality of the extracted features Different types of pooling are max pooling and average pooling. Therefore, convolution and pooling work together as a feature generation filter. Extracting features mainly involves things like pooling and convolution.

Classification:

A fully connected layer acts as a classifier, with each neuron providing full connectivity to all learned features map obtained from the last layer. This can be implements using flattening, that transform all pooled images into a continuous 1D vector using the statement classifier.

VI. RESULT



VII. CONCLUSION

Protection of crop in organic farming is not an easy task. It relies on a thorough knowledge of the crop being cultivated and its potential pests, pathogens and weeds. In our system, a specialized deep learning model based on a specific convolutional neural network architecture was developed to detect plant diseases from images of healthy or diseased plant leaves. Our detector used images captured in situ by various camera devices and images collected from various resources. Experimental results and comparisons between different deep architectures using trait extractors show that deep learning-based detectors successfully detect different disease categories in different plants and find solutions for diseases of concern has been shown to be possible. Pests/disease are generally not a significant problem in organic systems because healthy plants living in good soil with a balanced diet have a greater ability to resist pests/disease. We hope that will make an exciting contribution to agricultural research.

The main goal of future work is the development of a complete system consisting of server-side components, including trained models, and applications for smart mobile devices. A picture of a leaf taken with a cell phone camera. The application aims to assist farmers (regardless of experience level) to detect crop diseases quickly and efficiently, and to facilitate decision making when using chemical

pesticide products and in addition, future work includes dissemination of the model by training it to detect plant diseases over a wide area, combining aerial imagery of orchards and vineyards captured by drones, and aerial imagery for object detection. Contains convolutional neural networks. By expanding this research, the authors hope to make and influence the crop quality for future generations.

REFERENCES

1]. Aakanksha Rastogi, Ritika Arora, Shanu Sharma, "Leaf Disease Detection and Grading using Computer Vision Technology &Fuzzy Logic," presented at the 2nd International Conference on Signal Processing and Integrated Networks (SPIN), IEEE, 2015, pp. 500–505.

[2]. Garima Tripathi, Jagruti Save, "AN IMAGE PROCESSING AND NEURAL NETWORK BASED APPROACH FOR DETECTION AND CLASSIFICATION OF PLANT LEAF DISEASES," Int. J. Comput. Eng. Technol. IJCET, vol. 6, no. 4, pp. 14–20, Apr. 2015.

[3]. S. Arivazhagan, R. Newlin Shebiah, S. Ananthi, S. Vishnu Varthini, "Detection of unhealthy region of plant leaves and classification of plant leaf diseases using texture features," Agric Eng Int CIGR J., vol. 15, no. 1, pp. 211–217, Mar. 2013.

[4]. Prof. Sanjay B. Dhaygude, Mr.NitinP.Kumbhar, "Agricultural plant Leaf Disease Detection Using Image Processing"IJAREEIE, vol. 2(1),pp. 599-602, January 2013.

[5]. K. Muthukannan, P. Latha, R. PonSelvi and P. Nisha, "CLASSIFICATION OF DISEASED PLANT LEAVES USING NEURAL NETW ORK ALGORITHMS," ARPN J. Eng. Appl. Sci., vol. 10, no. 4, pp. 1913–1918, Mar. 2015.