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Survey on Plant Leaf Disease Detection Using Deep Neural Network

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Abstract: *Agriculture has a significant effect on our lives. Agriculture is the primary economic sector in our country. Appropriate management results in a profit when it comes to agricultural goods. Farmers lack knowledge in leaf disease, resulting in decreased productivity. Detecting plant leaf diseases is critical since profit and loss are directly related to productivity. CNN is the answer for detecting and classifying leaf diseases. The primary objective of this research is to identify leaf diseases in apple, grape, maize, potato, and tomato plants. Plant leaf illnesses are monitored throughout broad fields of crops for disease detection, and therefore automatically detect certain characteristics of diseases for which medical treatment is available. Detection of plant leaf disease has a wide range of applications in a variety of sectors, including biological research and agriculture institutes. Plant leaf disease detection is a critical area of research because it has the potential to benefit huge fields of crops by automatically detecting disease signs as soon as they emerge on plant leaves.*

Keywords: Agriculture, economic sector, CNN, diseases, crops

1. Introduction

Modern technology has enabled humans to feed over a billion people. Climate change and plant diseases continue to threaten food security. Plant diseases threaten not just global food security, but also the livelihoods of smallholder farmers who rely on healthy crops. Smallholder farmers produce almost 80% of food in developing countries, while pests and diseases are widely blamed for 50% of output losses [1, 2]. Crop, plant, and fruit diseases can drastically impair productivity and quality [3]. Plants provide 80% of the human diet and contribute significantly to global food security. Plant pests and diseases threaten the vital role plants play in food security by destroying crops and lowering food availability and access [4]. Crop disease monitoring and management will be less costly and time consuming if new technologies for early detection are developed. Early identification of agricultural illnesses boosts output by allowing early implementation of disease-prevention measures. This is more successful than curative therapies since sick plants may show symptoms too late for therapeutic treatments. The instruments will not only increase production but also help reduce illnesses.

Due to their huge computing capability, high-resolution screens, and comprehensive built-in accessory sets, such as sophisticated HD cameras, smartphones in particular offer extremely unique techniques to assisting in illness identification. By 2020, it is commonly projected that the world will have between 5 and 6 billion smartphones.

We required a significant, validated dataset of images of diseased and healthy plants in order to create reliable image classifiers for the purpose of diagnosing plant diseases [8]. Such a dataset did not exist however until recently, and even smaller datasets were not openly available.

Fig.1 Different Plants Leaves with Disease part

As seen in Figure 1, diseased portions of vegetable and fruit leaves such as potato, tomato, maize, apple, and grape may be easily diagnosed using deep learning algorithms.
Deep Learning's Role in Image Processing All other machine learning techniques work in the same way: they take the training database, evaluate new input and information, and make choices [5]. Deep learning, on the other hand, works with neural networks and can come to its own conclusions without the requirement for labelled training data. This strategy can be used by a self-driving automobile to distinguish between a signboard and a pedestrian. The output of one algorithm is sensitive to the outcome of another algorithm in a neural network, which uses algorithms that are present in the network side by side. This results in a system that can make decisions as if it were a person. As a result, we have a model that is a wonderful example of a machine learning system.

2. Related Work

A smart farming system that utilises necessary infrastructure is an innovative technology that allows the country's agricultural produce, particularly tomato, to improve in both quality and quantity. Because tomato plant production considers a range of factors such as the location, soil, and amount of sunlight, disease is unavoidable. Deep learning-enabled developments in computer system technology have cleared the way for camera-captured tomato leaf disease. This research developed a new approach for detecting sickness in tomato plants. A motor-controlled photo capturing box was built to record four sides of each tomato plant in order to diagnose and distinguish leaf diseases [6]. The Diamante Max tomato cultivar was chosen as the test subject. Phroma Rot, Leaf Miner, and Target Spot were the three diseases for which the approach was developed. Plant leaves, both damaged and healthy, are included in the dataset.
The network is then trained to recognise three ailments using a deep convolutional neural network [12]. To assess which tomato diseases were present on the observed tomato plants, Convolutional Neural Networks were used. The F-RCNN trained anomaly detection model had an accuracy of 95.75 %, whereas the Transfer Learning [15, 16] sickness recognition model had an accuracy of 80 percent. The real-time use of the automatic picture capture technology resulted in a 91.67 % detection rate for tomato plant leaf diseases [17].
Agriculture has a significant effect on our lives. Our economy's most vital segment is agriculture. Farmers have a hard time identifying the leaf disease, therefore they produce less. Videos and photos of leaves, on the other hand, give a better perspective for agricultural experts who can supply a better answer. As a result, the problem of crop disease can be solved. It's important to remember that if a crop's yield is low, it's unlikely to provide adequate nourishment. Because to advancements in technology, equipment are now capable of recognising and detecting plant illnesses. Recognize illnesses sooner so they can be treated, reducing the impact on harvest. The focus of this research is on applying image processing techniques to identify plant illness. This article employed semi-supervised approaches for crop kinds and disease detection in four classes to access an open dataset of 5000 images of healthy and diseased plant leaves [20].
The five varieties of apple leaf disease discussed in this study are aria leaf spot, brown spot, mosaic, grey spot, and rust. In apple, this is a problem. Deep learning techniques were employed in this study to improve convolution neural networks (CNNs) for disease detection in apple leaves. The apple leaf disease dataset (ALDD) is utilised in this article to design a novel apple leaf disease detection model that leverages deep-CNNs by employing Rainbow concatenation and Google Net Inception structure. The suggested INAR- model was trained on a dataset of 26,377 photos of apple leaf disease and then utilised to detect five prevalent apple leaf diseases. The INAR- SSD model achieves 78.80 % detection performance in the experiments, with a high-detection speed of 23.13 FPS. The findings show that the innovative INAR-SSD model is a high-performance solution for the early detection of apple leaf illnesses that can identify these diseases in real time with more accuracy and speed than earlier techniques [1].
Khirade S. [10] propose several segmentation, feature extraction, and classification approaches [13] for identifying and detecting illness types utilising the sick picture for classification. The system's leaf image was pre-processed by something that enhanced the image by conducting histogram equalisation. Different segmentation algorithms, such as K-Means clustering, have been presented to get the impacted region. The feature was then retrieved and computed using GLCM from the segmented region. Diseases may be recognised using artificial neural networks (ANN) or back propagation neural networks after feature extraction. The disadvantage of utilising K-Means clustering to segment the image is that the procedure is only semi-automated because the user must manually identify the cluster that includes the diseased region.
F. Molina et al. [7] proposed a color-based technique for detecting bacterial blight disease or any other type of infection on tomato leaves. The approach provided by the author is based on the classification of tomato leaves using colour descriptors. Color characterization is accomplished through the use of colour structure descriptors, such as a colour histogram that quantifies the amount of significant colour using the Hue-MaxMin method, scalable colour

descriptors, such as leading spatial colour distribution and colour layout description, or colour pattern variation using the YCbCr colour space transform. To improve the classification ratio, an unique procedure based on nested leaf one out crossvalidation is utilised once all of these characteristics or descriptor values have been calculated. An inner loop permit is used to evaluate specific descriptor configurations, while the out loop assesses performance across diverse descriptors. The colour structure descriptor, according to the author, gave greater accuracy than previous techniques.

K Muthukannan et al. [14] established a fuzzy rule-based approach for the categorization of tomato leaf disease utilising the colour characteristic. To begin, the gradient operator is employed to reduce noise or tiny functions in the image during preprocessing. In the last step, two crucial characteristics, mean and standard deviation, are retrieved from a cropped image with various image size samples. The picture region was identified as healthy and significantly impacted disease section of the plant leaf using a fuzzy inference method employing fuzzy rules with specified colour characteristics [19]. Whereas orange denotes a healthy area of the image, yellow and red denote a leaf that has been severely damaged. The performance of fuzzy rule-based categorization, according to the author, is adequate. The results of the experiments suggest that the proposed technique can identify leaf illnesses with a minimum of computing effort.

Shen Xizhen and his associates (2021) Edge detection technology is a vital piece of equipment in the field of image processing. In response to the problem that current frugal algorithms are unable to effectively discover picture edges when the image's adaptive capacity is limited, this study proposed an improved frugal edge detection approach. The application employs complex filtering algorithms to denoise the image. Using the four-way gradient template supplied below, calculate the gradient amplitude. Finally, the high and low thresholds of the images are calculated using image block processing and the largest inter-class variance (Otsu) approach. The results show that the revised frugal technique performs better in terms of noise reduction and can properly recognise plant leaf edge information than the prior version of the algorithm [19].

Jadhav S. [9] utilised GoogleNet and AlexNet models to train 54,306 images from the plant village website, with GoogleNet outperforming AlexNet with a higher training accuracy. However, when the model is evaluated using photographs obtained under settings other than those used to train it, the accuracy drops to 31.4 % in this research. they employed a 75/25, 60/40, and 70/30 percent train test split distribution using three types of image types: RGB colour images, grayscale images, and segmented images in this investigation.

Olana et al. [11] developed a deep learning strategy to identify wheat ret diseases on leaves. The experiment's authors chose three forms of diseases: yellow rust, leaf rust, and stem rust. Images are acquired from three Ethiopian agricultural research institutes, including Kolomsa Agricultural Research Institute, Bishoftu Agricultural Research Institute, and Ambo Agricultural Research Institute, for picture capture. they builds a MosNet model based on CNN architecture using RGB, Grayscale, and colour segmented images as pre-processing images. Disease classification is done with CNN and has a high accuracy of 99.76, but due to a lack of dataset, this article only has two classes: healthy and illnesses.

3. Conclusion

In this article, we discussed the fundamentals of deep learning and provided a detailed assessment of contemporary deep learning research in plant leaf disease identification. Deep learning algorithms are capable of identifying plant leaf diseases with high accuracy if sufficient data is supplied for training. The importance of large datasets with high variability, data augmentation, transfer learning, and visualization of CNN activation maps in improving classification accuracy, as well as the importance of small sample plant leaf disease detection and hyper-spectral imaging for early plant disease detection, has all been discussed. At the same time, there are certain shortcomings. The majority of the Deep Learning frameworks proposed in the literature show good detection effects on their datasets, but not on other datasets, indicating that the model is not resilient. As a result, increased robustness to adapt to the various illness datasets, deep learning models are required.

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