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A Review of Deep Learning Techniques for Automated Plant Leaf Disease Detection in Agriculture

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Abstract - Agriculture is a primary source of livelihood for a large population in India and remains essential for human survival and national economic development. However, variations in climate and local environmental conditions increase the risk of crop diseases, which can significantly reduce yield and quality. In many cases, the earliest symptoms of plant infections appear on leaves and, if not detected in time, the disease can spread throughout the plant and across the field, leading to major production losses. Early and accurate identification of plant diseases is therefore critical for reducing agricultural losses and improving the quality of farm produce. Since manual inspection is difficult and time-consuming due to the large number of plants in cultivation areas, automated disease detection methods are increasingly required. This work proposes an AI-based software approach for detecting leaf infections to enable fast and reliable diagnosis, followed by evaluation and actionable insights to prevent large-scale crop damage. The proposed framework involves key steps including image dataset collection, image preprocessing, feature extraction/selection from leaf images, model evaluation, and disease classification. The overall goal is to support timely disease management and improve crop productivity and profitability.

Keywords - Deep Learning, Plant Disease Identification, Plant Health Assessment.

INTRODUCTION

Agriculture has become essential not only for human survival but also for national growth and economic stability. In India, agriculture employed more than half of the population in 2018 and contributed approximately 17–18% to the country's GDP [1]. As global population continues to increase while the number of farmers gradually declines, maintaining and improving agricultural productivity has become increasingly important to ensure food security and sustain economic development.

Crops are frequently affected by diseases due to variations in weather, soil conditions, and local environmental factors. These diseases can reduce plant growth, cause excessive leaf drop, lower product quality, and ultimately decrease overall yield. In many cases, infections spread rapidly through seeds, insects, or microbial agents. Common causes of crop diseases include fungi, bacteria, viruses, and pests. Therefore, timely and accurate disease identification is critical for protecting crop quantity and quality. If plant diseases are not detected and managed early, they can damage large cultivation areas, negatively affect national development, and contribute to food shortages, increased hunger, and inflation.

Before the widespread adoption of information technology, plant disease detection relied largely on manual inspection using the naked eye. This approach requires experienced plant experts, repeated field visits, and continuous monitoring, making it costly and inefficient for large-scale farms [2]. Moreover, many farmers may lack the expertise to recognize specific diseases or pests accurately, and manual diagnosis can be inconsistent. As a result, incorrect pesticide use may occur, leading to reduced productivity and unnecessary losses. Manual monitoring is also time-consuming, labor-intensive, and impractical for large agricultural regions.

To address these limitations, automated plant disease detection systems are increasingly valuable, particularly for early disease diagnosis across large fields. Most automated approaches rely on detecting visible symptoms on plant leaves, such as single or multi-colored spots, abnormal color changes, leaf-shape deformation, early or late blight/scorch patterns, and brown or yellow lesions. Automated detection can improve accuracy, reduce time and labor requirements, and provide a more practical solution for large-scale farming environments.

II. LITERATURE SURVEY

Many analysts have collectively contributed to the achievement of the goal of plant disease detection through the use of advancements in technologies and computational capability, such as artificial intelligence, image pre-processing, machine learning, deep learning, transfer learning, genetic algorithms,

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big data, the Internet of Things, and so on. There are various limitations to the models that have been offered. Because the data pre-processing is difficult, and the selection of characteristics is dependent on the model, the accuracy of illness diagnosis is not always high, even when analysing a large range of pests and diseases, according to the authors.

Ghaiwat et al. (2014) "Detection and Classification of Plant Leaf Diseases Using Image Processing Techniques" (Detection and classification of plant leaf diseases using image processing techniques) "Several classification approaches, such as artificial neural networks, super vector machines, self-organizing maps, and fuzzy logic, were used in the study's classification. They discovered the k-nearest-neighbor strategy is the least difficult and typically plausible among the variety of computations for class prediction. If the training information is not separable, then it will be difficult to determine the optimal parameter in a super vector machine [3, for example].

Adhikari Santosh and colleagues (2018) published "Tomato Diseases Detection System Using Image Processing" in Scientific Reports "the data set contains 520 images of tomato leaves with three different leaf diseases, including Bacterial Canker (111 examples), Gray spot (113 examples), Late Blight (121 examples), and healthy tomato leaf images. Based on the plant village dataset, they were able to attain an accuracy of 89 percent with their method. There is a restriction in that this method can only identify three types of illnesses and one healthy plant at the same time. [5] To identify different types of illnesses, data must be trained on the present model in order to detect them.

Wu Jianyu and colleagues (2019) "Detection of Crop Pests and Diseases Using Deep Convolutional Neural Network and Improved Algorithm", in Proceedings of the National Academy of Sciences of China. A machine learning technique combined with sophisticated architecture AlexNet and GoogleNet - is used to diagnose plant illnesses in this research work, which is published in the journal Plant Disease. The author has put in a lot of effort into presenting a network that is reliant on transfer learning and information-development and that enhances the accuracy of identification and hence increases its effectiveness. In this study, 38 different kinds of normal and diseased leaf samples were utilised. The model proposed here is complicated, and it requires a quicker rate of convergence [6].

Sardogan Melike and colleagues (2018) published "Plant Leaf Disease Detection and Classification Using CNN with LVQ Algorithm" in Nature Communications. For the purposes of plant health assessment and disease detection, this model makes use of the CNN classifier. The author has utilised a dataset of 500 photos in this model, with 20% of the images being used to test the proposed model and the remaining 80% being used to train the system. They found a total of 5 classes of plant leaves for categorization, one of which was healthy and the other four of which were contaminated. They have employed pictures of 512x512 pixels in size, which are fairly good, and have used the R, G, and B channels matrix for the CNN contribution, with the result being fed into the Learning Vector Quantization algorithm. It was possible to achieve a normal precision of around 88 percent. This technique was shown to be suitable for identifying tomato-specific disorders[4].

Using a Convolutional Neural Network model, Hyeon Park et al. (2017) published "Image-based disease diagnosing and prediction of the crops by the deep learning mechanism." The model was utilised for leaf disease detection in their paper. The author has only completed a restricted categorization of strawberries that are healthy and free of powdery mildew. Infected flowers, foliage, and fruits are susceptible to powdery mildew, a moderate disease. The author has employed a relatively limited dataset of just 500 images for his research. The system consists of two convolutional networks and three fully linked networks, which are used to identify illnesses of the strawberry leaf. On a CPU, this model achieves an overall accuracy of 89.7 percent. The images in this model have been reduced to 227x227 pixels, and the objective function is being used to train the model.

Saradhambal.G. and colleagues (2018) "Detection and Treatment of Plant Diseases Using Image Classification" is the title of the paper. The Otsu classifier and the K-means clustering approach were utilised in this model. By employing the segmentation approach, this model was able to analyse the affected portion of the leaf. With the use of a feature extraction and classification technique, it can distinguish between healthy and sick leaves on the plant and categorise them accordingly. In this paradigm, the integrated voice navigation system is responsible for guiding the user through the whole procedure. They have not mentioned the accuracy that was attained with the suggested technique, nor have they discussed how tiny the dataset was.

III. PRAPOSED METHEDOLOGY

It is intended to analyse and diagnose plant disease using the suggested deep learning algorithm, which is based on deep learning algorithms. This Model includes leaf retrieval, picture segmentation, and identification, all of which are accomplished via the use of a focused deep learning algorithm.

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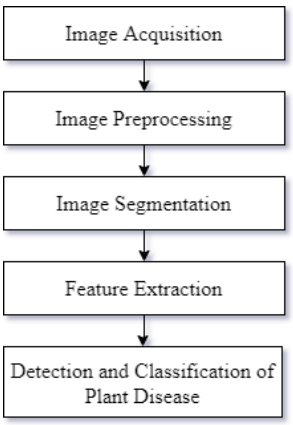

Figure 3.1 The basic procedure of the proposed approach

Image Acquisition

The initial stage in this strategy is to acquire data from the publicly available repository (see Figure 1). Various types of plant leaves are included in this dataset, including healthy leaves as well as samples of leaves that have been harmed by a disease or insect attack. This phase prepares the picture for further processing by importing it.

Image Preprocessing

The noise from the input image is removed during this step, which involves the use of noise filtering algorithms. Water spots, spores, and dust on the picture leaf surface may be present as noise, which may be used to alter the pixel values. For the purpose of speeding up the calculating process, input photos are reduced in size and deformity is removed when possible. When the smoothening filter is used, image distortion is reduced to a minimum.

Image Segmentation

The purpose of segmenting a plant leaf is to separate the image from its backdrop and arrange it into several components. Image segmentation may be accomplished in a variety of ways. The K-mean clustering and the Otsu classifier algorithms are used in this stage, during which segmented pictures are grouped into separate sectors according to our suggested model. The LAB colour model has the advantage of being able to cluster the segmented picture with ease, and as a result, the RGB colour model is turned into the Lab colour model. The segmentation process is used to extracted features detected on plant leaves, such as segment, borders, and color-related data, which are then used to create segments [11].

Feature Extraction

Images include a wealth of information about their contents, and they also carry descriptions of some unique qualities that may be used to distinguish between the categories of images in the given pattern. The colour co-occurrence approach will be used in the Feature Extraction strategy. Color, shape, and surface of the leaf are taken into consideration while extracting features. Using three significant number sequences, the colour co-occurrence approach may be used. First, it transforms photos in RGB format to images in Hexadecimal colour space (HIS). A colour co-occurrence matrix for H. S. I. is then created by using each pixel map.

Detection and Classification of Plant Disease

The extracted characteristic was used in this classification procedure to distinguish between infected and healthy plant leaves. Detailed information about the leaves and their associated features may be found in the feature dataset. For the classification process, it makes use of the Minimum distance Criterion and Deep learning CNN classifier. The retrieved characteristics of the plant leaves include homogeneity, contrast, energy, standard deviation, correlation, variance, and mean. These extracted features are delivered to the convolutional neural network, which utilises the target data as a class vector. It is possible to determine whether a certain plant leaf is healthy or sick during the classification process, according to model architecture.

Model Architecture

The input layer, output layer, and hidden layer are the three primary components of the CNN model architecture [4]. The convolution layer, fully connected layer, pooling layer, activation functions, and usually rectified units (ReLUs) layers are the most important components of the hidden layer.

The number of layers utilized in their arrangement and introduction of other image processing units varies from one architecture to a different determining their specificity.

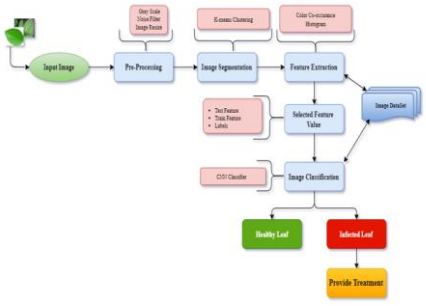

Figure 4.1 Proposed Model for plant disease detection

AlexNet

The CNN architecture grows in size in tandem with technological advancements in hardware. Among the layers in

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AlexNet's structure are one SoftMax, two normalisation layers, three max-pooling layers, two fully connected layers, and five convolutional layers[16]. Among the convolutional layers are convolutional filters, frequently corrected unit layers, and a nonlinear activation function, all of which are included in every layer. The pooling layers are in charge of performing the maximum pooling. Because it contains completely linked layers, the size of the inputs remains constant. In this model, there are sixty million different parameters.

GoogleNet

The structure of GoogleNet contains 27 pooling layers and 22 deep layers and 9 inception modules linearly stacked. After the inception modules, it is attached with the global average pooling layer. GoogleNet has about 4 million parameters.

Expected Outcome

One of the main objectives of this model is to accurately analyze and diagnose plant diseases to support healthy crop growth. The proposed system identifies plant diseases using a plant health assessment framework driven by a deep learning algorithm.

This study aims to develop an innovative solution for early-stage plant disease detection to improve crop productivity and enhance agricultural output in farming environments. The proposed model is built using deep learning techniques to overcome the limitations of manual disease identification, which is often time-consuming, expensive, and less reliable due to limited expertise and inconsistent judgment. Overall, the goal is to design a faster, more accurate, and practical approach for early plant disease detection and improved plant health management.

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