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# Detection and Classification of Plant Disease with Deep Learning

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***Abstract: Deep learning is a branch of artificial intelligence. In recent years, with the benefits of automatic learning and feature extraction, it's been wide involved by educational and industrial circles. It has been wide utilized in image and video processing, voice processing, and natural language processing. At a similar time, it's conjointly become an enquiry hotspot within the field of agricultural plant protection, such as plant disease recognition and pest range assessment, etc. the application of deep learning in disease recognition will avoid the disadvantages caused by artificial choice of illness spot options, make plant disease feature extraction additional objective, and improve the analysis potency and technology transformation speed. This paper provides the analysis progress of deep learning technology within the field of crop plant disease identification in recent years. during this paper, we tend to present this trends and challenges for the detection of plant leaf disease with deep learning and advanced imaging techniques. we tend to hope that this work are going to be a valuable resource for researchers UN agency study the detection of plant diseases and bug pests. At a similar time, we tend to conjointly mentioned some of the challenges and issues that require to be resolved.***
***Keywords: Deep Learning, Disease Detection, Classification, Artificial Intelligence, Leaf Disease Detection;***

## I. INTRODUCTION

The circumstance of plant diseases has a pessimistic impact on agricultural production. If plant diseases are not discovered within the time period, food uncertainty will increase [1]. Early detection is the basis for efficient prevention and control of plant diseases, and they play a important role in the management and decision making of agricultural production. In recent years, plant disease detection has been a crucial issue.

Disease-infected plants usually expose obvious spots or lesions on leaves, stems, flowers, or fruits. Generally, each disease or pest condition shows a particular pattern that can be used to recognize abnormalities. Usually, the leaves are the basic source for detecting plant diseases, and many symptoms of diseases may start to appear on the leaves [2].

In many of the cases, agricultural and forestry specialist detect on-site or farmers recognize fruit tree diseases and pests based on experience. This method is not only subjective, but also lengthy, laborious, and ineffective.

The farmers who have no experience may mis-judgment and use drugs blindly during the detection process. Quality and outcome will give pollution, which will be reason of economic losses. To respond these problems, research into the use of image processing techniques for plant disease detection has become a hot research topic. The general process of using traditional image recognition processing technology to detect plant diseases is shown in Fig. 1.

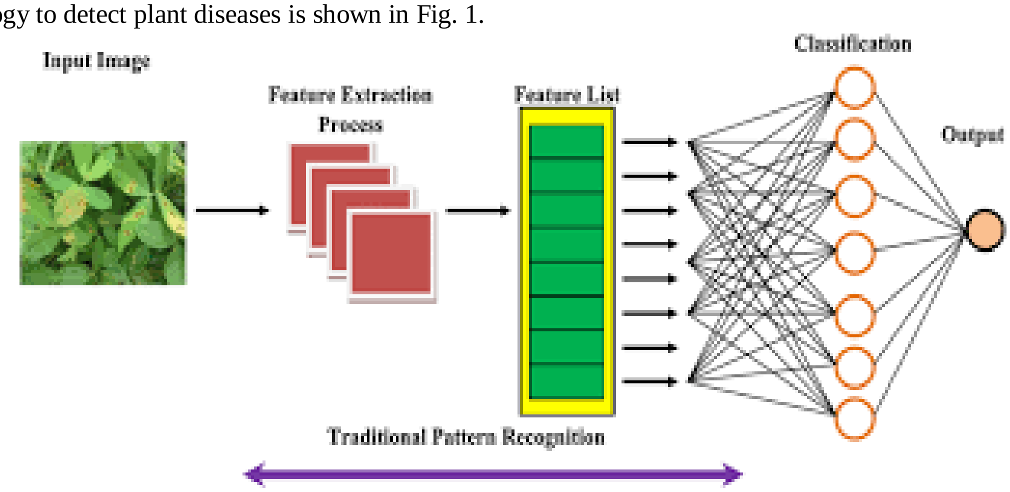


Fig 1. Traditional image recognition process.

## II. LITERATURE SURVEY

In the research of Dubey and Jalal [3] the K-means clustering method is used to segment the lesions regions, and they used combined the global color histogram (GCH) color coherence vector (CCV) local binary pattern (LBP), and completed local binary pattern (CLBP) to extract the color and texture features of apple marks, and they detected three types of apple diseases.

The authors Chai et al. [4] studied four diseases of tomato leaf, that include early blight and late blight leaf mildew and leaf marks, and they extracted 18 characteristic parameters such as color, texture, and shape information of tomato leaf spot images, using stepwise discriminant and Bayesian discriminant principal component analysis (PCA), respectively. The two methods named as Principal component analysis and fisher discriminant were used to extract the characteristic parameters and they constructed the discriminant model. 5 types of apple leaf diseases are selected by Li and He [5] as the objects of research. By extracting 8 features of the apple leaf spot image, such as color, texture, and shape. The BP neural network model was used to classify and recognize the diseases. The extraction of 63 parameters including texture features of rice leaf disease spots, color ,morphology, and, and applied step-based discriminant analysis by Guan et al. [6] and Bayesian discriminant method is used to classify and recognize three rice diseases (blast, stripe blight, and bacterial leaf blight) with the higher recognition accuracy of 97.2%.

The special of deep learning techniques names as convolutional neural networks (CNN), are quickly becoming the preferred methods [7]. The most popular classifier for image recognition is CNN, that shown ability in image processing and classification [8]. Plant image recognition based on leaf vein patterns [9] introduced Deep learning concept.

A deep learning model which is used to recognize 14 crop species and 26 crop diseases are trained by Mohanty et al. [10]. An accuracy of 99.35% on the test set is achieved trained model. A deep CNN is used to conduct symptom-wise recognition of four cucumber diseases (i.e., downy mildew, anthracnose, powdery mildew, and target leaf spots) by Ma et al. [11]. A system based on CNN to identify cucumber leaf disease, which realized an accuracy of 94.9% introduced by Kawasaki et al. [12].

## III.LEAF DISEASE DETECTION SYSTEM

In an era once good agricultural technology is therefore advanced, mobile phones became a replacement way ‘‘farming tool’’ for farmers, which may facilitate farmers in recognize diseases and insect pests. Currently, researchers develop small programs or mobile apps to assist farmers determine crop pests and diseases. The farmer takes photos and uploads the diseased parts of the crop, and therefore the system can come back the identification result at intervals some seconds. and supply users with the diagnosis results, similarity, unwellness characteristics, causes, and prevention and control plans for users, so farmers can treat diseases and insects during a scientific manner and increase crop yields. The Faster R-CNN by increasing the size of the input layer from 32 × 32 pixels to 600 × 600 pixels are modified by Ozguven and Adem [13]. And they developed an automatic identification and recognition system for leaf marks disease in 3 steps of sugar beet disease severity (mild, moderate, and severe).

An improved ResNet50 model (CDCNNv2) combined with deep transfer learning and developed a classification system for the severity of crop diseases and insect pests proposed by Yu et al. [14] . In addition to realtime and fully automatic identification of crop pests and diseases, the system also developed a series of supporting functions such as prevention and control recommendations and drug recommendations. The attention mechanism with the residual structure to build the PARNet model and completed the development of the WEB application are combined by Li et al. [14]. The average accuracy of the platform for 5 tomato leaf diseases can reached 96.84%. It was 2.25%∼11.58% higher than other models (VGG16, ResNet50, and SENet).

The convolutional neural network structure redesigned and optimized by Jiang et al. [16] based on the traditional LeNet-5 network, and they proposed a convolutional neural network system for identification of ginger disease based on the four types of ginger disease that are collected in the natural environment. The identification rate of four types of ginger diseases reached 96%.

5 types of apple leaf diseases are identified by Zhou [17] that are based on transfer learning and the Faster R-CNN and they developed an apple leaf disease recognition system based on the Android platform. The detection system had an average recognition accuracy of 76.55% for apple leaf diseases.

The MobileNet network on the mobile phone are deployed by Liu et al. [18], and the average recognition accuracy of the 6 type of grape diseased leaves gathered in the field was 87.5%, and the average calculation time for a single picture was 134ms.

Esgario et al. [19] developed a system that can recognize and estimate the severity of stress caused by biological agents on coffee leaves that are based on the ResNet50 architecture . The system had an accuracy of 95.24% for the classification of biological stress on coffee leaves, and an accuracy of 86.51% for estimation of the severity.

An automatic image segmentation algorithm proposed by Xiong et al. [20] based on the GrabCut algorithm and are selected the MobileNet as DL classification model, and they designed a crop disease detection system for mobile smart devices. The system had a identification accuracy of more than 80% for a total of 27 diseases of 6 crops in the laboratory environment and the field.

## IV. CONCLUSIONS

In this paper, we have presented a comprehensive review of recent research work done in plant leaf disease recognition using deep learning. Provided sufficient data is available for training, deep learning techniques are capable of recognizing plant leaf diseases with high accuracy. The importance of collecting large datasets with high variability, data augmentation, transfer learning, and visualization of CNN activation maps in improving classification accuracy, and the importance of small sample plant leaf disease detection and the importance of hyper-spectral imaging for early detection of plant disease have been discussed. Most of the DL frameworks proposed in the literature have good detection effects on their datasets, but the effects are not good on other datasets, that is the model has poor robustness. Therefore, better robustness DL models are needed to adapt the diverse disease datasets.

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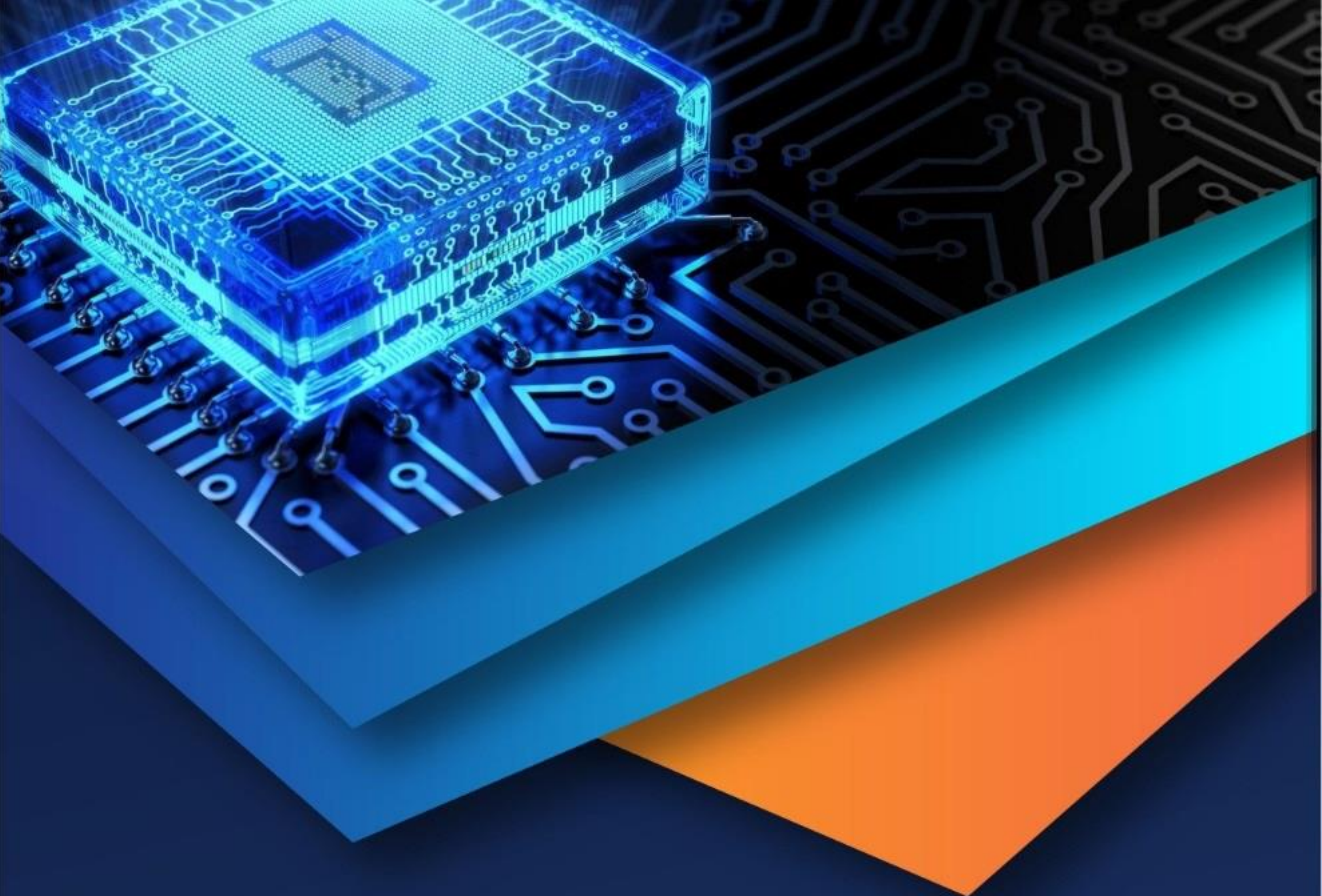


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