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Review on Leaf diseases detection using Deep learning

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***Abstract*— Agriculture is the most critical part of the Indian economy so to prevent production loss, disease attacks must be predicted and treated early. In plants with differing climatic conditions, disease is very normal and natural which decreases the crop productivity. Study into the use of image processing techniques for plant disease identification has become a hot subject in order to address these issues. Deep learning (DL) is the golden age of machine learning (ML), and it is now helping to identify and classify plant diseases early. This review investigates and analyzed recent methods on Deep learning, Transfer learning and convolution neural network for crop disease detection. First, a look at the deep learning architectures, data sources and various image processing techniques that were used to process the imaging data. Many DL architectures have recently been adopted, along with visualization tools, which are critical for identifying signs and classifying plant diseases. We also go through some of the unsolved issues that must be tackled in order to create functional automated plant disease recognition systems that can be used in the field.**

Keywords*— *Plant disease, Disease identification, Feature Extraction, Plant leaf Symptoms, Deep Learning, Transfer Learning, Convolution Neural Network.

I. INTRODUCTION

Plant diseases occur in agriculture as a result of weather change & variations in climate patterns of different places. Crops can become infected by bacterial, fungal and virus infections as a result of weather changes such as insufficient / extreme raining & excessively hot/ cold weather. A plant disease causes harm to the crop and reduces its quality and productivity. As a result, farmers face a difficult challenge in producing the highest crop quality and quantity. Crop disease detection is still a problem for plant production & crop development. Initial diagnosis of these different diseases allows for the implementation of preventative measures and the reduction of economic and productivity losses [1]. Leaf disease can be identified by signs such as spotting, brown dots, yellow dots, and so on, while monitoring can be accomplished by ensuring that the dots do not appear again in crops such as wheat, rice, oat, Pomegranate, cabbage, tomato, and so on. Farmers used their eyes to detect the disease much of the time, although this is an inefficient & unreliable procedure in the agriculture field. Identifying the condition may also necessitate the assistance of specialists. The availability of automated processes for such operations allows for more accurate disease detection, which lowers farmer prices and reduces the need for sufficient manpower. This research is concerned with a review of previous work undertaken in this period and the discovery of study gaps in order to offer a clearer result for plant leaf disease recognition [2]. Some of the sample images of the diseased crop are displayed in figure 1.


(a) (b) (c)

Fig.1. Sample image of Plant Disease (a) Maize Common Rust, (b) Rice White Tip, (c) Rice Leaf Scald [3]

The below is a summary of the paper's structure: The section 2 discusses the various plant leaf diseases. The steps for diagnosing a disease are described in Section 3. Section 4 includes work that has already been completed in the discovery of plant diseases. Section 5 addresses unresolved challenges in the current survey so, in order to achieve effective plant disease identification systems, these issues must be resolved. Observation Discussion and Conclusion is described in section 6 and 7 respectively.

II. SYMPTOMS AND DISEASES OF PLANT LEAVES

Various bacteria, fungi, viruses, phytoplasma, nematodes, viroids, & other agents cause plant diseases. Scab, Rot, Bacterial-blight, Bacterial-blot, Bacterial-wilt, Scab, and other diseases are caused by bacteria. Some diseases are caused by fungi, such as Grey-mold, Aphids, Downy-mildew, Cylindrocladium, Powdery-mildew, Mealy-bugs, Mosaic, Spotted-Wilt, and Curly-top. Any plant has certain distinguishing characteristics that enable us to recognize diseases caused by viruses, bacteria or fungi. The disease's effects are used to determine which disease it is and why it exists. Plant pathology is a branch of biology that studies plants and their diseases. Furthermore, it involves the investigation of responsible pathogens, their mechanisms, and strategies for controlling or managing plant diseases and minimizing their effects on plants. Any plant has certain distinguishing characteristics that enable us to recognize the disease, whether it is caused by bacteria, fungi, or virus**.** The disease's symptoms are used to determine the real disease and its cause.

III. STEPS FOR DIAGNOSING A DISEASE

Plant or leaf disease reduces the crop's production & efficiency. The most critical part of agriculture is disease control. The recognition of plant diseases is divided into five steps shown in figure 2: 1) Image collection, 2) Image preprocessing, 3) Image Segmentation, 4) Feature extraction, and 5) Image classification.

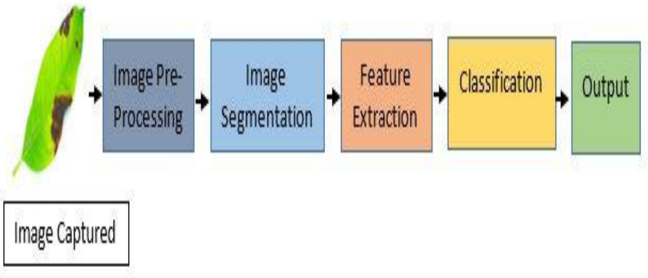

Fig.2. Disease Identification Steps[4]

1) Image Collection: For image analysis, images are captured via a webcam, mobile device, or smart camera that is positioned at a fixed or variable distance [4].

2) Image preprocessing: Picture resizing, picture smoothing, increased contrast, and image enhancement are some of the techniques used to eliminate noise and undesired objects from the image.

3) Image Segmentation: The Otsu method, K – meaning, Converting RGB to HIV, Converting RGB to HSV, and other approaches are used to divide a picture into multiple parts of the same feature [5][6] .

4) Feature extraction: Using techniques such as a Global color histogram (GCH), Local binary pattern (LBP), features such as color, shape, edge, texture, and so on are extracted at this stage[7].

5) Image Classification: To detect a specific disease on a leaf, image classification methods such as support vector machines, artificial neural networks, backpropagation, and convolution neural networks are utilized. After feature extraction, this method is applied to the photos [8][9].

This Convolutional Neural Network extracts picture data automatically and is programmed to recognize which characteristics are essential and which are not. Using convolution and pooling processes, CNNs can automatically learn the characteristics of pictures at multiple levels. Color and light come first, then local information like margins, corners, and lines, before moving on to more detailed facts and structures like texture and geometry. The first element of a CNN architecture is the input layer; the second part is a combination of n convolutional layers and a pooling layer; and the third portion is a fully connected multi-layer perceptron classifier. Figure 3 depicts the steps involved in utilizing a convolutional neural network to analyze images.

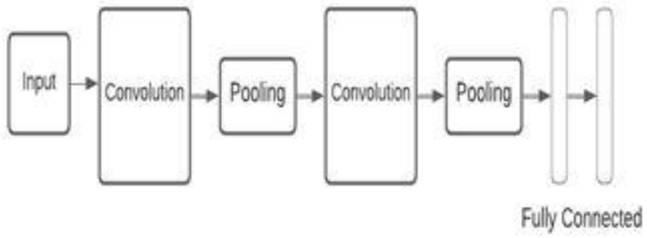

Fig. 3. Convolution Neural Network[10]

IV. RELATED WORK

[11] The models described in this research demonstrated the capabilities of modern CNN architectures. Furthermore, the dataset was divided into three categories: RGB images, Monochrome images, and Segmented Images. Separate methods were used to process all different types of information, with final accuracy ranging from 85.53 percent to 99.34 percent.

[12] For leaf disease identification, a deep convolutional network approach was used in combination with a classification system. According to a study climate change can affect stage and pathogen growth rate. To differentiate the surroundings of leaves, a trained deep neural network was used. Both photographs are manually cropped to illustrate the area of interest by creating a square around the leaves. To expand the dataset, the author used an augmented method. Rotations, transformations, and affine transformations are also examples of augmentation. Caffe was introduced as a deep CNN structure in this article.

[13] The authors used a broad dataset of "14,828" photographs of tomato-leaves which are infected with 9 diseases in this analysis. The CNN is used as a learning algorithm to train the classifier in this study. One of the most significant benefits of CNN is the automated retrieval of features from raw images. Deep models, especially CNNs, outperform previous work in the classification of tomato diseases, according to the findings. Author also suggested the usage of occlusion methods to help humans perceive the disease by locating unhealthy areas. The aim is to reduce the computation and size of deep models for small devices like mobile phones in the future. Furthermore, function visualization is a hot subject of deep learning & may be used to better understand crop diseases**.**

[14] Instead of using the occlusion process, the authors suggested using saliency charts. The use of guided backpropagation, which only allows positive gradients to propagate through the backward-pass, has been shown to minimize noise- activations in "saliency maps". The guided backpropagation saliency map was seen to be faster and more precise than the occlusion strategy by the authors. The findings of this assessment explicitly demonstrate that with a modern CNN architecture like inceptionV3, which obtained a 99.76

percent accuracy. The saliency map approach is adopted in this sense for locating disease-infected regions of the plant after disease diagnosis.

[15] The parameters of a CNN model and a Faster R-CNN architecture were changed in this study to create an Updated Faster R-CNN architecture for automated detection of sugar beet leaf spot disease. The procedure, which was suggested for imaging-based expert systems to diagnose disease seriousness, was trained and evaluated with 155 photographs, and the overall accuracy score was determined to be 95.48 %, according to the test results. To increase disease detection accuracy, further research should be performed for various deep learning algorithms that have been trained with a larger amount of data.

[16] There are three convolutional and three maximum pooling layers in this model, followed by two totally connected layers. The experimental findings demonstrate the proposed model's efficiency over pre-trained models such as InceptionV3, MobileNet and VGG16. The classified accuracy ranges from 76 percent to 100 percent depending on the class, and the proposed model's average accuracy is 91.2 percent for the nine disease and one healthy class. The proposed model requires approximately 1.5MB of storage space, while pre-trained models need approximately 100MB, demonstrating the proposed model's advantage over pre-trained models.

[17] Deep CNN transfer learning was investigated, and the network structure was modified to increase the learning capability of tiny lesion symptoms. Both the pretrained "MobileNet-V2" and the "classification activation map" (CAM), which was used for visualization as well as plant leaf lesion positioning, were chosen in this process. This paper proposes the use of a new deep learning design is called as Mobile-Net-Beta to recognize plant or leaf disease types. The transfer learning capabilities of deep CNN was investigated, & the standard Mobile-Net-V2 was updated to improve the learning ability of tiny lesion functions. The first phase only learned the parameters for new advanced layers from scratch, while the convolutional layers were fixed with the parameters learned on "Image-Net"; the second phase loaded the pre-trained model from the first phase and retrained all the parameters using the target dataset.

[18] The Efficient-Net deep learning methodology is proposed in this paper for the classification of crop diseases, and its efficiency is compared to that of state-of-the-art deep learning models. Transfer learning was used to train the Efficient-Net architecture and other deep learning models. The proposed architecture was compared to state-of-the-art deep learning architectures for detecting plant leaf disease in terms of performance. The original and updated copies of the Plant Village dataset were then included in the experiments. The plant leaf disease dataset will be extended in the future by expanding the number of classes and increasing the variety of the plants. This would help in the creation of models capable of making more precise forecasts in difficult scenarios. If these sophisticated models are used in mobile settings, plant pathologists & farmers may be able to quickly identify plant diseases and take effective action.

[19] The effectiveness of a pre-trained ResNet34 model in identifying crop disease is studied in this research. The proposed model, which is available as a web application, can detect seven plant illnesses in healthy leaf tissue. The model was deployed online after fine-tuning a pre-trained Convolutional Neural Network. A detailed analysis reveals the model's strengths and limits. When tested in a controlled setting, the accuracy is said to be 97.2 percent. In this scenario, augmentation and transfer learning were advantageous to the model, allowing the CNN to generalize with more reliability.

[20] The purpose of this research is to present an unique approach for detecting plant leaf diseases. Image segmentation and image classification are the two aspects of the procedure. For the symptom segmentation of plant disease photos, a hybrid method based on HSI and LAB is presented and applied. The author then creates a network architecture and a ConvNet-based model for picture categorization, inspired on AlexNet.

V. UNRESOLVED CHALLENGES

i). Not enough sources of acquiring large dataset: The key issue in training deep learning systems for plant disease detection is a lack of massive, well-annotated image datasets with a high degree of variability [21][22]. PlantVillage & the Image Database of "Plant Disease Symptoms (PDDB)" are the two big databases that are officially freely accessible. However, gathering data from the field is time-consuming, costly, and necessarily requires the use of domain experts for accurate annotation.

ii). Implementation of compact deep learning model for automatic disease detection: The majority of literature-based deep learning solutions used well-known CNN architectures like GoogLeNet, Alex-Net, Inceptionv3, ResNet, and VGG . This is due to a shortage of large enough datasets to train customized CNN architectures from scratch for plant disease detection. ''How many layers and how many neurons are ideal at last?" asked [3]. This problem forces researchers who wish to build custom CNN classifiers to use a trial-and-error approach to determine the best performing architecture. Compact CNN models will be in high demand, particularly in robotics, mobile applications, and embedded systems where real-time efficiency and low computational costs are needed.

iii). Pests & diseases on other areas of the crop may be identified: Until now, researchers have focused their efforts on disease identification and recognition on the leaf's upper side. The recognition of disease from images of flowers, fruits & stems has gotten little attention. Faster R-CNN networks have been suggested as a tool for detecting various diseases on tomato plants at different locations. The techniques, while extremely accurate, necessitate painstaking dataset labeling and annotation [23][24].

iv). Anomalies with visually related signs should be recognized: If the signs presented by various anomalies are visually identical, the classifier can be unable to differentiate among them [25]. There are currently no findings that integrate these new sources of evidence into the disease detection method in the existing work.

Table 1. COMPARATIVE EVALUATION OF DEEP LEARNING MODEL

Article	**Plant**	**Disease Or Deficiency**	**Architecture Used**	**Deep Learning Framework**	**Dataset**	**Scope and Limitation**
[11] 2016	Apple, Blueberry, cherry, Corn, Grape, Orange, Potato, Soyabean	Black Rot, Powdery Mildew, Gray Leaf Spot, Late Blight, Bacterial Spot etc..	AlexNet, GoogLeNet	Caffe	There are 54,306 photographs in the PlantVillage data collection, with 38 groups of 14 crop species and 26 diseases.	The model's accuracy is reduced by 31% when tested under condition other than images
[12] 2016	Apple, Peach, Pear, Cherry	Downy mildew, powdery mildew, Rust	CaffeNet (AlexNet)	CaffeNet	Images were gathered from the Internet and scanned for by disease and plant name in a variety of languages	Obtaining photographs for the purpose of enriching the collection and enhancing the model's accuracy by various fine-tuning and augmentation techniques.
[26] 2017	Apple	Deficiency of potassium and magnesium, Glomerella stains	AlexNet	Caffe	1450 Collected images from apple trees (Maxigala, Fuji Suprema and Pink Lady)	Accuracy obtained with healthy and unhealthy leaves only
[27] 2017	Cassava	Cassava brown streak, Green mite damage, mosaic disease, Brown leaf spot, Red mite damage	Inception v3	TensorFlow.	11,670 cassava images acquired from field in Tanzania	Background fluctuations had little effect on the model's prediction accuracy.
[13] 2017	Tomato	Bacterial Spot, Early Blight, Late Blight, mosaic Virus, Yellow Leaf Curl Virus	GoogLeNet, AlexNet	DIGITS	Open access repository of images Plant village dataset	The computation time is longer, and there is room to shrink the size of the deep model for compact devices like smartphones.
[14] 2018	14 crop types, 38 disease classes, and healthy plants	Late Blight, Septorial Leaf spot, Late Blight, Leaf Mould	Inceptionv3, VGG13, DenseNet169 , AlexNet	pyTorch	PlantVillage dataset	The goal is to concentrate on creating a robust labeled dataset that will enable us to quantify the efficiency of saliency map visualization numerically.
[15] 2019	Sugar beet	Leaf spot disease	Faster R-CNN	Matlab	Self-acquired sugar beet 155 images	To increase disease detection accuracy, research should be performed on various deep learning algorithms on larger amount of data.
[16] 2020	Tomato	Bacterial spot, Early Blight, Late Blight, mosaic Virus, Leaf Mold	VGG16, InceptionV3 and MobileNet	Keras	Plant village dataset	Model need to be modified with other crops and larger number of images.
[17] 2020	Rice, Maize	Rice stack-burn, rice leaf-smut, rice white-tip, Maize Eyespot, Gray Leaf Spot.	MobileNet-V2	Matlab	Plantvillage database	Real world scenario need to be considered for experiment
[18] 2021	Apple, cherry, Grape, Potato	Powdery mildew, black measles, late blight, bacterial spot	EfficientNet	Keras	Plant village dataset	To increase the plant diversity and number of groups in the plant leaf disease dataset

VI. DISCUSSIONS

In the survey it has been observed that

Observation 1

A convolutional neural network was used in the majority of the experiments to classify diseases in plants such as corn, oil palm, wheat, soybean, strawberry, cucumber, pomegranate, rice, and potato. Similar CNN models have been used to diagnose disease in a variety of vegetables and fruits. Figure 4 depicts some of the literature that was used to classify the subdomains in the field of agriculture during this research [28],[29],[30].

Observation 2

The majority of the researchers used existing libraries to capture 133,158 photographs, with just 29,301 images obtained in the field. This suggests that existing models depend on online databases rather than photographs captured in real-world scenarios [11],[20],[21]. Following this discovery, it was determined that these CNN models were not properly trained and tested using

Images gathered from the real world under a variety of climatic conditions. The efficiency of CNN models cannot be determined using the standard datasets used for the majority of studies. According to the current paper, existing CNN models can only be conditioned and validated with image datasets collected from the field during the crop life cycle. Because of the bigger training and testing datasets, the overall results of the model's performance are not predicted.

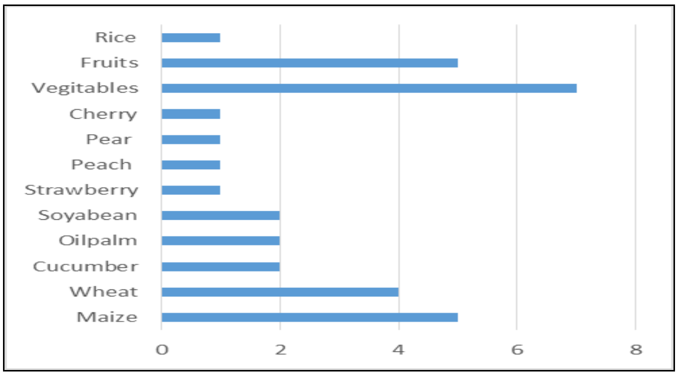

Fig.4. CNN models on different subdomains of agriculture

Observation 3

AlexNet, GoogLeNet, DenseNet169, MobileNet, InceptionV3, MobileNet-V2, EfficientNet, VGG13, Faster R-CNN, and VGG16 are the leading CNN technologies used to create the models. [31] According to the findings, 86 percent of current models are ineffective in identifying and classifying diseases. According to the findings, current models need to be improved in terms of development and deployment in order to achieve higher levels of accuracy [32],[33].Figure 6 depicts some of the literature that was used to classify the different models in the field of agriculture during this research. Table 2 shows the comparative analysis of existing models which contains comparison based on crop, number of images, pre-trained models and their accuracy. Figure 5. depicts the comparative analysis graph based on the given data.

Table 2. Comparative Analysis of Existing Models

Crop	**Number of Images**	**Pre-trained Model**	**Accuracy**
Apple/Grape/Corn	54,306	Alexnet	85.53%
Cassava	15000	Inception V3	91%
Tomato	50,000	Googlenet	97.7%
Sugar beet	155	Faster R-CNN	95.48%
Tomato	50,000	VGG16	77.2%
Rice maize	54,306	MobileNet-V2	99.25%
Apple/Grape/Potato	55,448	EfficientNet	98.42%

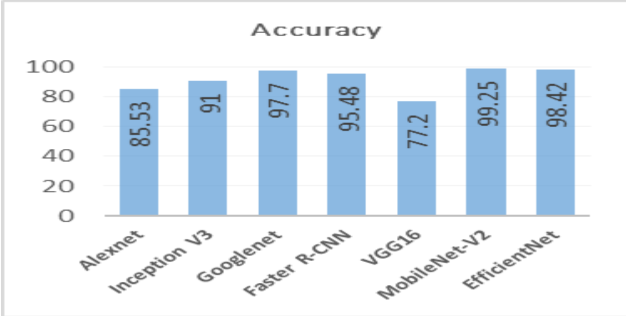

Fig. 5. Comparative Analysis of existing Model

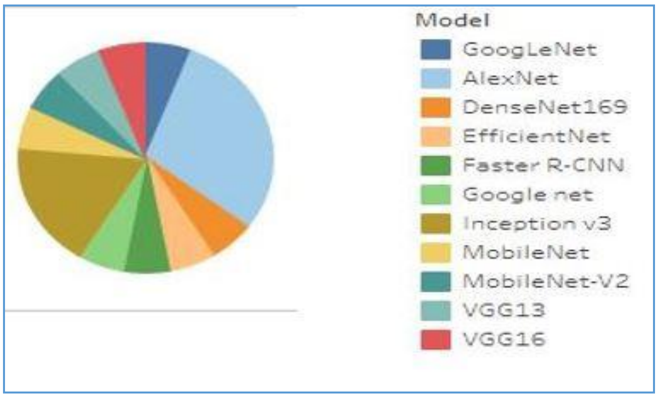

Figure 6. Usage of different CNN models in the survey

VII. CONCLUSION

A survey of deep learning strategies was conducted in this paper to determine how applicable they are in the agriculture domain. By studying the field of agriculture, 70 related papers were found during this work. We concentrated on the data sources, models used and analyzing the proposed CNN models overall performance. Though image processing and classification algorithms for plant disease identification are available, they are time consuming and can only handle limited synthetic datasets. The findings revealed that the majority of current CNN models were limited in their ability to handle unstructured images. Although there are image processing and classification methods for identifying plant diseases, they are time-consuming & only work with a small number of digital datasets. As a result, deep learning could be the best choice for improving the rate of leaf disease identification and classification accuracy.

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