CROP DISEASE PREDICTION USING DEEP LEARNING TECHNIQUES - A REVIEW

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Abstract

In agriculture, AI is bringing about a revolution by replacing traditional methods with more efficient ones and thereby contributing to a better world. Artificial Intelligence and machine learning are enabling the development and implementation of devices that can identify and control plants, weeds, pests and diseases through remote sensing. Plant disease lowers the quantity and quality of food, fiber, and biofuel crops, all of which are important to the Indian economy. In addition to reducing waste, using Deep learning technologies can increase quality and speed up market access for farmers. Here, we summaries recent crop disease detection research papers in a concise manner. In this research, multiple deep learning algorithms are used to demonstrate the current solutions for different crop disease diagnosis. I hope this report will be useful to other crop disease detection researchers.

Keywords:
Crop Disease, Deep Learning, CNN

1. INTRODUCTION

India economy cannot function without agriculture. Agriculture is essential to human survival since it provides the most useful products of human life, such as food, fruits, oil, and other nutrients. According to the 2011 Census, agricultural and allied sector activities employ 54.6% of the total workforce and provide 17.8% of the country Gross Value Added (GVA) in 2019-20.

The Indian government has made a number of initiatives to ensure that the country agriculture sector grows in a sustainable manner. Farmers' incomes have been boosted as a result of new initiatives. When it comes to crop disease, many people working in agriculture worries about how to cope with this dilemma without creating substantial environmental damage, which has plagued farmers for millennia.

Plant diseases were formerly detected with the naked eye, which was a time-consuming and labor-intensive process that required experts to manually monitor crop fields. Crop disease tracking should begin at an early stage in a crop life cycle and continue until the crop is ready for harvest. As a result of their devastating consequences on the food supply, crop diseases are considered every farmer worst fear. Crop disease is responsible for 20-40% of all crop losses in the global market every year. Leaf curling, powdery mildew and wilting are just a few of the most frequent diseases that affect plants.

Crop disease losses are predicted to cost the global economy $60 billion each year. In this research, multiple deep learning algorithms are used to demonstrate the current solutions for different crop disease diagnosis. In the next parts, you will find the rest of the paper. To begin, we'll go over the basics, then we'll go over the literature. Deep learning, history, and other topics are covered in the third section. Ultimately, the article ends with a look at what the future holds.

2. LITERATURE REVIEW

Zhou et al. [1] developed a restructured residual dense network has been suggested that combines the advantages of deep residual networks and dense networks, which minimizes the number of training process parameters while boosting the accuracy and flow of information and gradients in tomato leaf disease identification. A 95% success rate on the Tomato test dataset was achieved in the AI Challenger 2018 datasets. These scientists reworked the RDN model used by Super-resolution. A dense layer is utilized for classification following normalization, optimization of the RDB tensor, and addition of the convolution residual module. There was a 95% success rate for the RRDN on the tomato dataset, which was deemed adequate.

Zhang et al. [2] developed an upgraded version of the faster RCNN is proposed to identify healthy tomato leaves For the extraction of picture features, they use a depth residual network instead of VGG16 in order to gain more detailed information on the disease. In order to cluster these bounding boxes, the k-means technique is utilized According to the clustering results, they strengthen the anchoring. Three distinct feature extraction networks are used to conduct a k-means experiment. Faster RCNN exhibited a 2.71% lower accuracy rate in detecting agricultural leaf disease than the upgraded approach.

Khattak et al. [3] developed an example of a CNN model Two convolutional layers was used in the suggested CNN model. There are a number of illnesses that affect citrus fruits and leaves, such as black spot, scab, greening, and Melanose, that can be categorized by the first convolutional layer. This technique can tell if citrus trees are healthy or ill based on their fruit and foliage. Using photographs of citrus fruits and foliage, this CNN model proposes to classify diseases. The three key components of the proposed model, as detailed below, are data collection, data pre-processing, and CNN model application. The suggested CNN classifier had a 95.65% accuracy rate in citrus fruit/leaf disease classification trials compared to other classifiers.

Ai et al. [4] developed a convolutional neural network to diagnose crop diseases automatically. The Inception-ResNet-v2 model is based on deep learning theory and convolutional neural network technology. Twenty-seven photos of illnesses in ten different crops were made available as part of the 2018 AI Challenger Competition. Inception-ResNet v2 was utilised as a training model for training purposes. The model now includes cross-layer direct edges and multi-layer convolution. The ReLu function is activated when the convolution process is complete. An experiment revealed that this model had an overall accuracy of recognition of 86.1%. A Wechat applet for detecting crop illnesses and insect pests was created using this model once it had been trained. The hybrid network model can be used to identify and detect plant diseases and insect pests more precisely than the old approach.

Ahmad et al. [5] presented a system for classifying symptoms of plant disease based on their individual observations and observations of others. Transfer learning can be used to train small datasets with weights derived from a larger dataset. Negative transfer learning, on the other hand, is a major source of concern when it comes to transfer learning. When knowledge is transmitted between domains, a stepwise transfer learning strategy can prevent overfitting and negative transfer learning. A dataset on pepper disease and PlantVillage (a publicly available dataset) were both provided as training and assessment datasets for this system by the National Institute of Horticultural and Herbal Science, Republic of Korea. For the Pepper dataset, the suggested model had an accuracy of 99.99%, while for the PlantVillage dataset, it had an accuracy of 99.699%.

To better understand tomato leaf diseases like spots and yellow leaf curl, Ding Jiang et al. [6] turned to deep learning. The Resnet-50 residual network was the starting point. Illness categorization was produced using iterative learning using convolutional layers that automatically extracted the leaf disease position feature. Because of the risk of over-fitting, random data augmentation was employed in the experiment. The network was reconfigured by using a Leaky-ReLU activation function and an 11×11 convolution kernel. As a result of iterative learning, the proposed strategy accuracy in training and testing was enhanced by 0.6% and 2.3% (98%).

Liu et al. [1] developed an adversarial network-based leaf disease identification model was developed. DenseNet and instance normalization were utilized in the training of the network and then used to recognize illness images and extract characteristics from grape leaf lesions. Finally, the training process was stabilized by imposing a steep regret gradient penalty. “A successful GAN-based data augmentation strategy helped researchers overcome the problem of overfitting in disease identification, and it also helped to enhance detection rates.

Pham et al. [1] developed with the use of an artificial neural network (ANN) technology, it is possible to detect early diseases on plant leaves by analyzing high-resolution pictures of the disease blobs. Segmenting the infected blobs of the dataset is the final step after the dataset has been pre-processed using a contrast enhancement method. Using a hybrid metaheuristic-based wrapper-based feature selection technique, blobs are represented by a set of measurement-based features. When deciding on these attributes, the model performance is taken into account.

Table.1. Summary of recent research work of detecting plant disease using Deep learning

Model	**Crop**	**Disease**	**Technique used**	**Classifier**	**Performance (Accuracy)**
[9]	Soybean	Bacteria disease, Downy mildew, Spider Mite, with pest, with pesticide, virus disease	CNN, Google Net, Alex Net, ResNet 50, augmentation, transfer learning	CNN	CNN with ResNet50 94.5%
[10]	Millet	Mildew (plant dead, yellowing, malformation n of ear, planetule, partial green ear)	Transfer learning, Optimizer= Stochastic Gradient Descent (SGD), Early stopping technique, Image Net, VGG 16 MODEL	CNN	95%
[11]	cucumber	Powdery mildew	Semantic segmentation model based on convolutional neural networks Mostly used u-net architecture.	CNN	96.80%
[12]	Mango	*Anthracnose*	AlexNet architecture	MCNN	97.13 (higher on comparison with svm,rbfnn)
[2]	Tomato	Powdery Mildew, ToMV, LeafMoldFungus, Blight	K-mean algorithm and replace VCC-16 by deep residual network	Faster RCNN	2.71% higher
[8]	mango	Anthracnose, Gall Midge, Powdery Mildew	Used awrapper- based feature selection algorithm, which is built on a hybrid metaheuristic.	ANN	89.41%
[14]	Grape	black rot, esca and isariopsis leaf spo	United Model is designed to distinguish leaves with common grape diseases:googleNet and Resnet	CNN	97.13%
[13]	Citrus leaf	Phyllocnistis citrella , lack of element, scale insects	Two models used AlexNet and ResNet	CNN	95.83% and 97.92% for ResNet and AlexNet respectively.
[1]	Tomato leaf	EarlyBlightFungus, LateBlightWaterMold, YLCVVVirus, LeafMoldFungus, SeptorialLeafSpotFungus, TargetSpotBacteria	Combine deep residual and dense network	CNN	95%
[3]	Citrus fruit	Blackspot,Canker,Scab,Greening, Melanose	Multilayer convolution neural network	CNN	94.55%

An ANN is fed with the features that have been selected. Their findings are compared to those of a different technique, which includes the use of popular CNN models (AlexNet, VGG16, and ResNet-50). The findings of an ANN were found to be superior to those of a CNN with a simpler network configuration (89.41% vs 78.64%, 79.92%, and 84.88%, respectively). They claim that their method can be used on low-end devices like smartphones in order to assist farmers in the field.

3. DEEP LEARNING

Warren McCulloch and Walter Pitts developed a computer model based on human brain neural networks in 1943, which is when deep learning got its start. To imitate human reasoning, Warren McCulloch and Walter Pitts employed a mathematical and algorithmic approach they called threshold logic. There have been two important interruptions in the development of deep learning since then. Henry J. Kelley is credited with creating the fundamentals of the continuous back propagation model in 1960. As far back as 1962, the chain rule was all Stuart Dreyfus had to work with. Though it had been around since the early 1960s, back propagation didn't really come into its own until the mid-1980s.

A broader look at the history of Deep Learning reveals 3 major waves of advancements: Cybernetics - During 1940–1965; Connectionism - During 1980-1990 and Deep Learning - Since 2006.

1. Artificial intelligence (AI) and machine learning (ML) are both subsets of the term "deep learning. Utilizes computer techniques to do data processing and to create abstract models that can be used to model the mind workings.
2. In order to process data, understand human speech, and visually detect objects, Deep Learning employs multiple layers of algorithms. The output of the preceding layer serves as the input for the next layer in the chain. The input layer is at the top of a network, followed by the output layer. The 'secret layers" are all the ones in between. For the most part, the activation functions in each layer are basic and homogeneous.
3. Deep Learning also includes feature extraction. Extracting relevant "features" from data via an algorithm is used for training, learning, and understanding reasons.

3.1 INTRODUCTION TO DEEP LEARNING

It is possible to divide machine learning into subgroups. Similar to machine learning, deep learning uses both supervised and unsupervised learning. For the creation of AI, the human brain served as a source of inspiration. Artificial neural networks (ANNs) were the inspiration for deep learning, while ANNs were the inspiration for ANNs inspired by human biological neural networks (HBN). Deep learning, a machine learning technology, can be utilized to achieve this goal. A neural network will always have:

- **Information layer**: Pixels of an image or a time series data
- **Hidden layer**: Weights that are learned as the neural network is trained
- **Output layer**: The final layer mainly offers you a prediction of the input you fed into your network.

Since the neural network hidden layers are trying to learn parameters (weights) that, when multiplied by input, give you a predicted output that is close to what you want, it can be thought of as an approximate function.

3.2 DEEP LEARNING METHODS

Different ways exist for implementing deep learning. In order to get the most out of your data, it important to know what kind of task you're attempting to achieve with it and what kind of data you're dealing with. 'A person can choose the optimum strategy for a given problem based on these considerations. Here are a few ideas to get you started:

1) **Classical Neural Network**: Full-Connected Neural Networks, also known as multilayer perceptrons, are generally characterized by their multilayer perceptrons. Fran Rosenblatt, a psychologist from the United States, created it in 1958. The model is transformed into a fundamental binary data input via this process. Included in this model are three functions: Linear function, Non-Linear function and Rectified Linear Unit. This is suitable best for any table dataset which has rows and columns formatted in CSV, classification and Regression issues with the input of real values and any model with the highest flexibility, like that of ANNs.
2) **Convolutional Neural Network**: Artificial neural network (ANN) models have evolved into a more advanced and high-potential form known as CNNs. The software key tasks include preprocessing, data compilation, and dealing with growing levels of complexity. An animal visual cortex is organized in such a way that it is influenced by the structure of its neurons. One of the most versatile models for focusing on both image and non-image data, CNNs are worth a closer look". CNNs are built using input data that is initially convolutionally modelled:

- A feature map is created from input data, and then a function is applied to it.
- As an example, Max-Pooling helps a CNN identify an image depending on provided alterations.
- For a CNN to assess, the data collected in this stage must be flattened in this manner.
- When a model loss function is compiled, it is often referred to as a "hidden layer".

Suitable best for:

- Natural language processing (NLP) and image recognition (IR) are two of the many tasks that CNNs can be used for; they can also be used to analyze video and segment images.
- For speedier analysis, any two-dimensional input data that may be reduced to one-dimensional.
- Producing an output, the model must be part of its design.

3) **Generative Adversarial Network**: This algorithm uses a Generator and a Discriminator neural network deep learning approach. While the Generator Network produces bogus data, the Discriminator can distinguish between real and fraudulent. During the battle between the Generator and Discriminator, the Generator makes phoney data that

is identical to the real thing, while dissecting it to identify the difference. Data generated by the Generator network could be used to populate a picture library. Deconvolution neural networks would then be created. To discriminate between real and fake photos, an Image Detection network would then be deployed. Suitable Best for: Image and Text Generation, Image Enhancement and New Drug Discovery processes.

4) **Recurrent Neural Networks (RNN)**: It is a sort of Neural Network in which the output from the previous step is supplied as an input to a newer stage. Although all inputs and outputs in typical neural networks can be considered independent, there are some situations where prior words are required and therefore need to be remembered when predicting a sentence next word. With the use of a Hidden Layer, RNN was created to tackle this problem. When it comes to neural networks, the Hidden state of RNNs is the most significant and fundamental aspect. RNNs have a "memory" that retains all of the information they've learned. All the hidden layers or inputs are treated as if they were the same in order to produce the same result. There is a significant reduction in the number of parameters, unlike other neural networks. This is suitable for text data, speech data, classification prediction problems, regression prediction problems and generative models.

4. CONCLUSION

An overview of contemporary deep learning research into plant leaf disease recognition is provided in this publication, as well as an introduction to the basics of deep learning. In the literature, most DL frameworks are capable of detecting anomalies in their datasets, but their ability to detect anomalies in other datasets suffers from weak robustness. As a result, DL models need to be more robust in order to handle the wide range of illness datasets. The Plant Village dataset has been utilized in a slew of studies to gauge the accuracy of DL models. Many plant species and ailments are included in this dataset; however, they were collected in the laboratory. When applied to the actual world, this means a large amount of data on plant disease may be collected. It still a work in progress to apply HSI in the early detection of plant diseases, despite the fact that many DL frameworks and hyperspectral pictures have been used for this purpose in study. In other words, it is difficult to collect labelled datasets for early plant disease detection, and even experienced specialists are unable to define where the invisible disease symptoms are located and designate completely invisible disease pixels, which is essential for Agri coop to detect plant disease.

REFERENCES

[1] C. Zhou, S. Zhou, J. Xing and J. Song, "Tomato Leaf Disease Identification by Restructured Deep Residual Dense Network", *IEEE Access*, Vol. 9, pp. 28822-28831, 2021.

[2] Y. Zhang, C. Song and D. Zhang, "Deep Learning-Based Object Detection Improvement for Tomato Disease", *IEEE Access*, Vol. 8, pp. 56607-56614, 2020.

[3] A. Khattak, "Automatic Detection of Citrus Fruit and Leaves Diseases Using Deep Neural Network Model", *IEEE Access*, Vol. 9, pp. 112942-112954, 2021.

[4] Y. Ai, C. Sun, J. Tie and X. Cai, "Research on Recognition Model of Crop Diseases and Insect Pests Based on Deep Learning in Harsh Environments", *IEEE Access*, Vol. 8, pp. 171686-171693, 2020.

[5] M. Ahmad, M. Abdullah, H. Moon and D. Han, "Plant Disease Detection in Imbalanced Datasets Using Efficient Convolutional Neural Networks with Stepwise Transfer Learning", *IEEE Access*, Vol. 9, pp. 140565-140580, 2021.

[6] D. Jiang, F. Li, Y. Yang and S. Yu, "A Tomato Leaf Diseases Classification Method Based on Deep Learning", *Proceedings of Chinese Conference on Control and Decision*, pp. 1446-1450, 2020.

[7] B. Liu, C. Tan, S. Li, J. He and H. Wang, "A Data Augmentation Method Based on Generative Adversarial Networks for Grape Leaf Disease Identification", *IEEE Access*, Vol. 8, pp. 102188-102198, 2020.

[8] T.N. Pham, L.V. Tran and S.V.T. Dao, "Early Disease Classification of Mango Leaves Using Feed-Forward Neural Network and Hybrid Metaheuristic Feature Selection", *IEEE Access*, Vol. 8, pp. 189960-189973, 2020.

[9] Q. Wu, K. Zhang and J. Meng, "Identification of Soybean Leaf Diseases via Deep Learning", *Journal of The Institution of Engineers (India): Series A*, Vol. 100, pp. 659-666, 2019.

[10] S. Coulibaly and Kamsu-Foguem, "Deep Neural Networks with Transfer Learning in Millet Crop Images", *Computers in Industry*, Vol. 108, pp. 115-120, 2019.

[11] K. Lin, L. Gong and J. Pan, "Deep Learning-Based Segmentation and Quantification of Cucumber Powdery Mildew Using Convolutional Neural Network", *Frontiers in Plant Science*, Vol. 10, pp. 155-167, 2019.

[12] U.P. Singh, S.S. Chouhan, S. Jain and S. Jain, "Multilayer Convolution Neural Network for the Classification of Mango Leaves Infected by Anthracnose Disease", *IEEE Access*, Vol. 7, pp. 43721-43729, 2019.

[13] A. Luaibi and A. Miry, "Detection of Citrus Leaf Diseases using a Deep Learning Technique", *International Journal of Electrical and Computer Engineering*, Vol. 11, pp. 1719-1727, 2021.

[14] Miaomiao Ji, Lei Zhang and Qiufeng Wu, "Automatic Grape Leaf Diseases Identification via United Model based on Multiple Convolutional Neural Networks", *Information Processing in Agriculture*, Vol. 7, No. 3, pp. 1-13, 2020.