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Reviw Article

Crop Disease Prediction using Deep Learning Techniques - A Review

Gargi Sharma[1], Gourav Shrivastava[2]

[1,2]*School of Advanced Computing, Sage University Bhopal, M.P, India.*

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Abstract *- In agriculture, AI is bringing about a revolution by replacing traditional methods with more efficient ones and contributing to a better world. Artificial Intelligence and machine learning enable 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, which are important to the Indian economy. In addition to reducing waste, deep learning technologies can increase quality and speed up market access for farmers. Here, we summarize recent crop disease detection research papers. Multiple deep-learning algorithms demonstrate this research's current solutions for different crop disease diagnoses. I hope this report will be useful to other crop disease detection researchers.*

Keywords *- Crop Disease, CNN, Deep Learning.*

1. Introduction

India's 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. [24]According to the 2011 Census, agricultural and allied sector activities employ 54.6 percent of the total workforce and provide 17.8 percent of the country's Gross Value Added (GVA) in 2019-20. (at current prices). The Indian government has made several initiatives to ensure that the country's agriculture sector grows sustainably. Farmers' incomes have been boosted as a result of new initiatives. When it comes to crop disease, many people working in agriculture worry about coping with this dilemma without creating substantial environmental damage, which has plagued farmers for millennia. Plant diseases were formerly detected with the naked eye, a time-consuming and labor-intensive process requiring experts to monitor crop fields manually. Crop disease tracking should begin early in a crop's 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's worst fear. Crop disease is responsible for 20-40 percent of all crop losses in the global market annually. Leaf curling, powdery mildew, and wilting are some of the most frequent diseases affecting plants. Crop disease losses will cost the global economy $60 billion each year. Multiple deep-learning algorithms demonstrate this research's current solutions for different crop disease diagnoses. In the next parts, you will find the rest of the paper. First, we'll go over the basics, and 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

[1]Changjian Zhou[1], Sihan Zhou[2], Jinge Xing[3], and Jia Song[4] 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 percent success rate on the Tomato test dataset was achieved in the AI Challenger 2018 datasets. These scientists reworked the RDN model used by Superresolution. A dense layer is utilized for classification following normalization, optimization of the RDB tensor, and adding the residual convolution module. There was a 95% success rate for the RRDN on the tomato dataset, which was deemed adequate.

Future Work: Practical use of this work can be made to enhance agricultural intelligence.

[2]Yang Zhang[1], Chenglong Song[2], and Dongwen Zhang[3] - an upgraded version of the faster RCNN is proposed to identify healthy tomato leaves. They use a residual depth network instead of VGG16 to extract picture features to gain more detailed information on the disease. 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 percent lower accuracy rate in detecting agricultural leaf disease than the upgraded approach.

Future Work: To help build smart agriculture, complex diagnoses should include these aspects.

[3]Asad Khattak[1], Muhammad Usama Asghar[2], Ulfat Batool[2], Muhammad Zubair Asghar[2], Hayat Ullah[2], Mabrook Al-Rakhami[3], and Abdu Gumaei - an example of a CNN model Two convolutional layers was used in the suggested CNN model. A number of illnesses affect citrus fruits and leaves, such as black spots, scabs, greening, and

Melanose; the first convolutional layer can categorize that. This technique can tell if citrus trees are healthy or ill based on their fruit and foliage. This CNN model proposes classifying diseases using photographs of citrus fruits and foliage. As detailed below, the three key components of the proposed model are data collection, data preprocessing, and CNN model application. Compared to other classifiers, the suggested CNN classifier had a 95.65 percent accuracy rate in citrus fruit/leaf disease classification trials.

Future Work: However, new domains of citrus fruit disease recognition need to be researched, and they only utilize one deep learning-based CNN model, whereas other deep learning models can be used.

[4]Yong Ai[1,2], Chong Sun[1,2], Jun Tie[1,2], and Xiantao Cai[3] - Convolutional neural network automatically diagnoses crop diseases. 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 in the 2018 AI Challenger Competition. Inception-ResNet v2 was utilized as a training model for training purposes. The model now includes cross-layer direct edges and multilayer convolution. The ReLu function is activated when the convolution process is complete. An experiment revealed that this model had an overall recognition accuracy of 86.1%. Once trained, a WeChat applet for detecting crop illnesses and insect pests was created using this model. The hybrid network model can more precisely identify and detect plant diseases and insect pests than the old approach.

Future Work: To gather more information. Rice and wheat, as well as the associated disorders, were only studied in this study. As a result, the next step is to gather more crop species and illness photographs for future investigation. The model needs to be improved. Inception-resnet-v2 Using a mixed network like this, researchers could reap the experiment's benefits. However, this model is still worthy of further examination because of its high level of identification accuracy. Cropped photos need to be reliably classified by a network model.

[5]Convolutional Neuronnets-Moben Ahmad, Muhammad Abdulla, Hyeonjoon Moon, and Dongil Han have presented a system for classifying plant disease symptoms based on their observations and observations of others. Transfer learning can train small datasets with weights derived from a larger dataset. On the other hand, negative transfer learning is a major source of concern for transferring learning. A stepwise transfer learning strategy can prevent overfitting and negative transfer learning when knowledge is transmitted between domains. A dataset on pepper disease and PlantVillage (a publicly available dataset) was 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 percent, while the PlantVillage dataset had an accuracy of 99.699 percent.

Future work: Additional crops and illnesses can be studied using more advanced deep-learning techniques in practical applications. Cutting-edge research must focus on practical solutions to help both industry and consumers.

[6]Ding Jiang and his colleagues turned to deep learning to understand tomato leaf diseases like spots and yellow leaf curls better. 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 using a Leaky-ReLU activation function and an 11x11 convolution kernel. As a result of iterative learning, the proposed strategy's accuracy in training and testing was enhanced by 0.6 percent and 2.3 percent (98 percent).

[7]Bin Liu [1,2,3] (Member, IEEE), Cheng Tan[1], Shuqin Li[1,2,5], Jinrong He[4], and Hongyan Wang[5,6] - An adversarial network-based leaf disease identification model was developed. DenseNet and instance normalization were utilized in the network's training 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.

[8] Tan Nhat Pham, Ly Van Tran, and Son Vu Truong Dao-With 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 preprocessed using a contrast enhancement method. Using a hybrid metaheuristic-based wrapper-based feature selection technique, blobs are represented by measurement-based features. When deciding on these attributes, the model's performance is considered. An ANN is fed with the features that have been selected. Their findings are compared to different techniques, including popular CNN models (AlexNet, VGG16, and ResNet-50). An ANN's findings were superior to those of a CNN with a simpler network configuration (89.41 percent vs 78.64 percent, 79.92 percent, and 84.88 percent, respectively). They claim that their method can be used on low-end devices like smartphones to assist farmers in the field.

2.1. Future Works

- Increasing the number of layers, the number of hidden nodes, and the activation function of the MLP model.
- Using plantations to gather a more diverse variety of information.

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

Ref.No.	Crop	Disease	Technique used	Classifier	Performance (Accuracy)
[9]. (2019)	Soybean	Bacteria disease, Downy mildew, Spider Mites, with pests, pesticide, virus disease	CNN, Google Net, Alex Net, ResNet 50, augmentation, transfer learning	CNN	CNN with ResNet50 94.5%
[10]. (2019)	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]. (2019)	cucumber	Powdery mildew	The semantic segmentation model based on convolutional neural networks Mostly uses u-net architecture.	CNN	96.80%
[12]. (2019)	Mango	*Anthracnose*	AlexNet architecture	MCNN	97.13 (higher in comparison with svm, RBF NN)
[2]. (2020)	Tomato	Powdery mildew, ToMV, LeafMoldFungus, Blight	K-mean algorithm and replace VCC-16 by deep residual network	Faster RCNN	2.71% higher
[8]. (2020)	mango	Anthracnose, Gall Midge, Powdery Mildew	Used a wrapper-based feature selection algorithm built on a hybrid metaheuristic.	ANN	89.41%
[14]. (2020)	Grape	black rot, esca and isariopsis leaf spo	United Model is designed to distinguish leaves with common grape diseases: google net and Resnet	CNN	97.13%
[13]. (2021)	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]. (2021)	Tomato leaf	EarlyBlightFungus, LateBlightWaterMold, YLCVVVirus, LeafMoldFungus, SeptorialLeafSpotFungus, TargetSpotBacteria	Combine deep residual and dense network	CNN	95%
[3]. (2021)	Citrus fruit	Blackspot,Canker, Scab,Greening, Melanose	Multilayer convolution neural network	CNN	94.55%

3. Basic Knowledge of Deep Learning

3.1. [21]History

- When deep learning started, Warren McCulloch and Walter Pitts developed a computer model based on human brain neural networks in 1943. Warren McCulloch and Walter Pitts employed a mathematical and algorithmic approach they called threshold logic to imitate human reasoning. There have been two important interruptions in developing deep learning since then. Henry J. Kelley was credited with creating the fundamentals of the continuous backpropagation 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, backpropagation didn't come into its own until the mid-1980s.

- A broader look at the history of Deep Learning reveals 3 major waves of advancements:
  - Cybernetics — From 1940–to 1965
  - Connectionism — From 1980–to 1990
  - Deep Learning — Since 2006

- Artificial intelligence (AI) and machine learning (ML) are subsets of the term "deep learning. Utilizes computer techniques to process data and create abstract models that can model the mind's workings.
- Deep Learning employs multiple layers of algorithms to process data, understand human speech, and visually detect objects. The output of the preceding layer serves as the input for the next layer in the chain. The input layer is at the network's top, followed by the output layer. The "secret layers are all the ones in between. Most of the activation functions in each layer are basic and homogeneous.

1) Deep Learning also includes feature extraction. Extracting relevant "features from data via an algorithm is used for training, learning, and understanding reasons.

3.2. [22]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 the following:

- 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 feed into your network.

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

3.3. [23]Deep Learning Methods

Different ways exist for implementing deep learning. To get the most out of your data, it's 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:

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
- Rectified Linear Unit

Suitable best for:

- Any table dataset which has rows and columns formatted in CSV
- Classification and Regression issues with the input of real values
- Any model with the highest flexibility, like that of ANNS

[25]Convolutional Neural Network- Artificial neural network (ANN) models have evolved into a more advanced and high-potential form known as CNNs. The software's key tasks include preprocessing, data compilation, and dealing with growing levels of complexity. An animal's visual cortex is organized so that the structure of its neurons influences it. 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 modeled:

- A feature map is created from input data, and a function is applied.
- For 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.
- When a model's loss function is compiled, it is often called 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 analyze video and segment images.

- For speedier analysis, any two-dimensional input data may be reduced to one-dimensional.
- In producing output, the model must be part of its design.

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 phony data 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. An Image Detection network would then be deployed to discriminate between real and fake photos.

Suitable Best for:

- Image and Text Generation
- Image Enhancement
- New Drug Discovery processes

It is a Neural Network in which the output from the previous step is supplied as an input to a newer stage. Recurrent Neural Networks (RNN) Although all inputs and outputs in typical neural networks can be considered independent, there are some situations where prior words are required and must be remembered when predicting a sentence's next word. With 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 their learned information. All the hidden layers or inputs are treated as if they were identical to produce the same result. There is a significant reduction in the number of parameters, unlike other neural networks,

Suitable best for:

- Text data.
- Speech data.
- Classification prediction problems.
- Regression prediction problems.
- Generative models.

4. Conclusion

An overview of contemporary deep learning research into plant leaf disease recognition is provided in this publication as an introduction to the basics of deep learning. In the literature, most DL frameworks can detect 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 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, a large amount of data on plant disease may be collected. It's still a work in progress to apply HSI in the early detection of plant diseases, even though many DL frameworks and hyperspectral pictures have been used in the study. In other words, collecting labeled datasets for early plant disease detection is difficult. Even experienced specialists cannot define where the invisible disease symptoms are located and designate completely invisible disease pixels, which is essential for Agri coop to detect plant disease.

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