Deep learning methods for identifying diseases in plants: A survey

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November 10, 2021

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Abstract

Deep learning which can be considered as a subset of machine learning which again is a subset of artificial intelligence is a recent trend on which researches are being carried out. Deep learning and transfer learning are two different approaches connected with the process of identifying various plant illnesses. This research focuses on deep learning approaches and highlights current advancements in the application of these cutting-edge technology to agricultural disease picture recognition. The summary of deep learning approaches used to identify various illnesses in plants such as tomato, strawberry, peach, onion, corn, and so on...
Keywords: Deep Learning, Plant Disease Identification, Agricultural Diseases

1. Introduction

Agronomy is the mainstay of India's economic development. Agricultural sector is country's backbone, thus it's critical to maximise productivity from the field by spotting damaged plants early. A crop is being chose by a farmer based on several factors. It might be the type of the soil, climate and the market value of the crop. Industries have started to identify ways through which agricultural yield can be increased. Plant diseases are considered to be a challenge in the process of increasing yield and reducing economic loss. Hence disease identification needs more concentration in order to increase the yield.

Manual examination by farmers or professionals has been the conventional method of disease detection, but it is time consuming and expensive. The advancement of image processing methods has accelerated exertions to create computerized algorithms to detect crop illnesses based on observable signs on plants. These systems attempt to make farmer participation as simple as feasible while also ensuring that the identification/classification model is reliable. Deep learning models emerged later whereas research was carried out in disease identification and classification using image processing which is now being carried out by deep learning algorithms.[2]

In many nations and places, however, visual inspections by professionals or experienced farmers are still the predominant method for detecting plant diseases. This traditional strategy has numerous drawbacks, such as the time-consuming nature of manual inspections in large farms and the prohibitive cost of frequent expert consultations. As a result, the automatic detection of plant diseases, which tries to detect indications of plant diseases as soon as they emerge on leaves, is of enormous practical significance.[3]

Deep learning approaches have been effectively employed to address problems that are simple for people to solve, such as game play or object identification, but are difficult to mathematically explain or computationally prohibitively expensive.
Image recognition, in particular, has experienced a paradigm shift, with advancements sprouting up everywhere.[4]
CNN is considered to be the most effective architecture because of its ability to quickly comprehend visual content and hence aid classification. Depending on the architectural alterations, CNN can be classed into seven main categories. Many methods have been developed to improve CNN, including GoogLeNet, DAG Net, AlexNet, and others. [5]

Many earlier studies have looked at picture recognition, and a specific classifier has been utilised to categorise the images as healthy or unhealthy. The primary source of identifying a disease in a plant is its leaf. The indications of the disease can be seen on the leaf itself.

In previous decades, k-nearest neighbour (KNN), support vector machine (SVM), fisher linear discriminant (FLD), artificial neural network (ANN), random forest (RF) and other classification algorithms were widely utilised for identifying diseases in crops. Because of intricacy in sick leaf images, automatic recognition of plant disease photos remains a difficult task. Deep learning approaches, notably convolutional neural networks (CNNs), have recently risen to the top of the priority list for overcoming several obstacles. In both big and small scale challenges, classification is done by CNN especially when recognition of images is involved. It has demonstrated exceptional image processing and classification abilities.[6]

Training a model using CNN have enforced a Challenge. Number of inputs need to be large in order to train a model using CNN whereas collecting sufficient real time data becomes expensive and sometimes not possible. Furthermore, when deep learning algorithms are deployed in real-world scenarios, a variety of factors influence their performance. As a result, the practical application of technologies for automatic disease detection is currently limited. [7]

In this paper, we first see about the general structure of plant disease detection system followed by a review of articles related to the study. At the end we give a comparative study of the papers.

2. Related Work

Deep learning is a technique which allows many classifiers which uses linear regression as its base to work together after which any activation function can be applied. The difference between deep learning and traditional learning is the number of nodes present. Deep learning makes use of numerous nodes whereas a single node is present in the former one. These nodes collectively are termed as a neural network and each individual node is named a perception. In deep learning there can be any number of layers apart from the input layer and the output layer. Each layer comprises of neural units which can be hundreds or thousands in number.
There are layers called hidden layers which includes the nodes that are not part of neither the input layer nor the output layer. Another advantage in deep neural network is that the classifiers are generated by the network itself.

Applications of deep learning is wide and is effectively used in the area of image processing. Rest of the section gives the details about how deep learning is used in detecting agricultural plant diseases.

a. Plant Disease Detection System

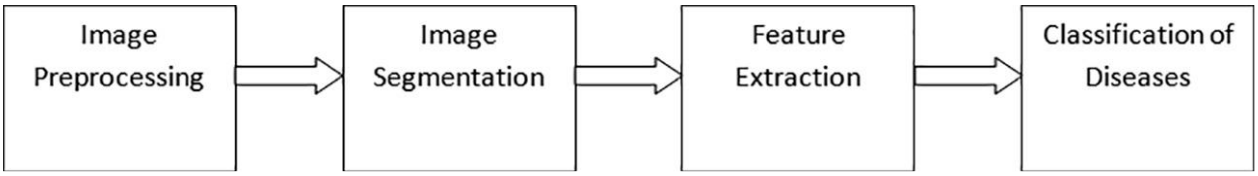

Fig 1. Plant Disease detection system

The plant disease detection system's step-by-step approach is depicted in Fig1[8] and can be understood as follows:
The first step seeks in improving the image captured in order to remove unwanted noise, update particular attributes required in subsequent processing. Geometric image transforms (such as scale, translation, and rotation) are classified as pre-processing techniques. The second step refers to a process which slices an image to many pieces. This phase's main goal is to categorise artefacts or extract other useful information from digital images. The next phase stresses on significant elements which, when shown effectively, provides the precise information needed for classification. Feature extraction techniques can be applied on object's geometry, shape or colour. Texture extraction is most extensively used technology in this area. Final phase determines whether the input can be classified into diseased or not. Classification algorithms can be used to identify images based on the features extracted from them.

b. Literature Survey

[9] briefs about a hybrid CNN framework that has 3 stages. In the first stage, feature extraction is performed by a pre-trained CNN model. Two subsequent layers, FC6 and FC7, are used to extract features. In the second step, a feature based fusion approach is used to merge the valuable features of the two subsequent layers. In addition, feature selection is done using PLS theory. For final recognition, the strong nominated characteristics are passed to numerous classifiers.
For each testing image, the final step in the procedure gives a labelled image.

[10] suggested a convolutional neural network model integrated with a loss function for identifying plants having disease of their own kind. The method integrates the benefits of two separate functions used for loss estimation, resulting in improved estimation. In last layer of the model, characteristics gathered from plant leaves were used to classify illnesses.
The Plant Village Database was utilised to obtain the data for this experiment. This approach was 98.93 percent accurate in distinguishing affected samples from unaffected samples. The results acquired through this model demonstrate that it is more effective than other existing approaches in classifying disease-affected leaf samples.

[11] proposed an algorithm for identifying wheat leaf diseases and their severity. The Otsu approach is used to separate disease spots in wheat leaf pictures based on disease dispersion features. To generate the training set, the optimal blend of colour along with texture attributes in the image with disease symptoms are done. The ideal elliptic metric matrix is generated, followed by sample feature space modification and eliminating feature correlation. The severity of the damage is then determined. According to results of the experiments conducted, the suggested approach achieves the greatest identification accuracy of 94.16 percent.

The training and valuation of various current Convolutional Neural Networks models for the categorization of illnesses of tomato plant was proposed [12]. For transfer learning, images in the publicly available dataset (PlantVillage) was separated into ten classes. For use in low-power devices, the chosen models have an architecture which is seperable in depths. Quality metrics and saliency maps are used to undertake quantitative and qualitative evaluation and analysis. Finally, a graphical user interface application was created.

New paradigm for tomato leaf disease recognition has been proposed[13]. Binary Wavelet Transform combined with Retinex (BWTR) is used to remove noise from the image and to enhance the image. This removes distortions while preserving significant texture information. The significant portions were then isolated from the background and was then optimised by the Artificial Bee Colony algorithm (ABCK). In the implementation part, the photos were identified using the B-ARNet model. The overall detection accuracy of 8616 photos is around 89 percent, according to the application findings.

An inevitable technique making use of image processing detects and categorises groundnut leaf diseases has also been used. For precise detection and classification, proposed technique H2K combines the detector, Histogram and a classifier. It consists of several processes, including image acquisition, image preprocessing with masking and segmentation to separate the diseased section, feature identification and extraction, and groundnut leaf disease classification using H2K. It is resilient, optimal to diagnosing groundnut leaf illnesses, enhanced performance producing 97.67 percent accuracy, according to data.[14]

From potato leaf photos, a precise recognition approach for detection of the illness kind and severity of damage was investigated. An approach is designed to efficiently and precisely segment the leaf from the photos. The texture characteristics are recovered and the colour features are pulled out. Finally, to assess the performance, various classifiers were used.[15]

To achieve coarse segmentation, a marker-based watershed technique is first utilised to distinguish significant portions from the unwanted portions. After the separation is done and new set of images were created, the images are labelled, separated into two categories: diseased and unaffected areas. Then, using a naive Bayes classifier, a classification model is developed to distinguish the specific aspects of patches based on their features. At last, the damage caused by the illness was determined by dividing the quantity of the disease's minimal circumscribed areas by the entire area of the wheat kernel. [17]

[16]Artificial Neural Network combined with an optimizer for disease diagnosis in tomatoes was employed. Prior to disease classification in tomatoes, FA is used to do colour image segmentation to achieve successful disease prophecy in the end. Furthermore, several

statistical parameters including accuracy were generated for analyzing performance of the suggested system.

Disease recognition for corn was done with the help of an improved dense convolutional neural network (CNN) architecture (DenseNet). Accuracy of DenseNet model was 98.06 percent. Furthermore, when compared to existing CNNs such as EfficientNet, VGG19Net, NASNet, and Xception Net[18], it needs substantially very less number of parameters. Two quality metrics (time and accuracy) were used to compare the optimised model with the other currently existing architectures.
Another technique for tomato leaves disease diagnosis that generates synthetic data of tomato plant leaves using the Conditional Generative Adversarial Network (C-GAN)[26] was proposed. Then, using transfer learning, a model was setup on experimental and simulated pictures to classify the inputs according to disease categories. On the publicly available PlantVillage dataset, the suggested model was thoroughly trained and tested. For categorization into five, seven and ten classes, suggested technique achieved accuracy of 99.51 percent, 98.65 percent, and 97.11 percent, respectively.

A simpler CNN model with eight hidden layers[20] outperforms classic algorithms on the publically accessible dataset PlantVillage, with 98.4 percent accuracy. The dataset contains 39 classes of various crops such as apple, potato, maize, grapes, and so on, with 10 classes of tomato illnesses. While k-NN has the best accuracy of 94.9 percent in classical ML approaches, VGG16 has the best accuracy of 93.5 percent in pretrained models. After image augmentation, picture pre-processing was employed to improve the performance of the proposed CNN. With an accuracy of 98.7%, the suggested model executes exceptionally sound on other datasets also.

Fully convolutional neural networks[21] are proposed by Lawrence C. Ngugi et al.,2020 to conduct background removal in photos collected through smart devices. In addition to other leaves and stalks, the leaf would be surrounded by numerous backdrop aspects. These background features are removed by the segmentation network, leaving only the target leaf. To train and evaluate the suggested networks, a dataset that is indicative of this scenario was created. KijaniNet, a segmentation network, outperforms all competitors.

[19] Wan-Soo Kim et al.,2020 presented a system for monitoring the crops automatically. A deep learning model was trained using weakly supervised learning strategy that simply uses image-level annotation to categorise and localise objects. It is excellent in identifying crop disease symptoms with a hazy borderline. Training the model was done by making use of the onion photos acquired by a field monitoring system, and it was divided into six classes, one of which was the disease symptom.

Three different methods focusing on regression and classification were developed to diagnose apple leaf diseases using DenseNet-121 deep convolutional network. For modelling and evaluating data, the apple leaf image data set was employed, which included 2462 photos of six apple leaf diseases. On the test set, the approaches achieved 93.51 percent, 93.31 percent, and 93.71 percent accuracy, respectively.[22]

[23] To condense the quantity of needless antifungal agent application and to detect powdery mildew (PM), a chronic fungoid ailment in berries deep learning was utilized. Many pretrained models are available and Net based architectures were among the well-known

learners optimised and evaluated in this work. To avoid overfitting and to account for the varied forms and directions of the target, data augmentation was performed on 1450 healthy and sick leaf pictures. The algorithms utilised had a classification accuracy of >92 percent on average (CA).

3. Results and Discussion

As a result of reading the papers related to disease identification and classification, it is noted that various crops and algorithms are considered and each algorithm is evaluated on different performance metrics. The following table1 illustrates the comparative study of the papers with respect to algorithms used and the performance metrics used. It is seen that most of the models have made use of the same architecture as their base and the scope of collecting manual datasets have also increased.

Table2 consolidates the parameters used to measure the performance. When a different crop is chosen, different metric to define performance were also used. Some articles make use of one metric and some articles rely on more metrics to prove the performance. Such metrics for a single crop from different articles are consolidated to highlight the metrics that can be used as a measure of performance.

Sl.No	Crop Chosen	Architecture Used	Dataset Used
1	Apple	Deep Convolution Network	AI Challenger- Plant-Disease-Recognition
2	Banana	Multispectral Image Classifier	UAV
3	Citrus	SqueezeNet	Manual
4	Corn	RNN	Manual
5	Groundnut	HOG+KNN	Manual
6	Onion	CNN	Manual
7	Peach	CNN	Plant Village
8	Potato	ANN	AI Challenger
9	Strawberry	CNN	ImageNet
10	Tomato	CNN	Plant Village
11	Wheat	SVM	Agricultural Institutes

Table1. Comparison of Architecture and dataset used

Sl.No	Crop Chosen	Performance Metrics
1	Apple	Precision, Sensitivity, F1 score
2	Banana	IoU, Precision, Recall

3	Citrus	Accuracy, Precision, Recall, F1 score
4	Corn	Accuracy, Precision, Support, F1 score
5	Groundnut	Classification Accuracy
6	Onion	IoU
7	Peach	Accuracy, Precision, Recall, F1 score
8	Potato	IoU
9	Strawberry	Precision, Sensitivity, Specificity, F1 score
10	Tomato	Accuracy, Precision, Recall, F1 score
11	Wheat	Identification Accuracy

Table2. Performance metrics used

4. Conclusion

Almost all deep learning algorithms effectively perform their tasks especially when it comes with working on images. CNN has proved itself as the best architecture in the area of image identification and classification. This advantage has been made use of in the systems to recognize and categorize the diseases in the area of agronomy.

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