IJNRD.ORG ISSN : 2456-4184
INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD) | IJNRD.ORG
An International Open Access, Peer-reviewed, Refereed Journal

PLANT AND FRUIT DISEASE DIAGNOSIS AND TREATMENT THROUGH DEEP LEARNING

[1]Dr Ram Paul, [2]Sachin Kumar, [3]Mayank Khandelwal, [4]Ishu Khandelwal, [5]Tushar Goyal
[1]Assistant Professor-II, [2]Students,
[1]Amity School of Engineering and Technology, Noida, India

ABSTRACT

It is critical to have control over plant disease since it influences the overall quality and number of species of the plants, plus the nation's infrastructure. To avoid revenue damage and the endangerment of particular species, automated detection and sorting of leaf illness is critical. In past, numerous machine learning (ML) models have been suggested to observe and treat plant disease; nevertheless, they are not accessible because of the difficulty of procuring advanced equipment, the restricted scalability of models, and the complexity and inefficiencies of their application. Local expertise and previous experiences have historically been used to diagnose plant pathogens. A plant's health may be determined by a qualified specialist. If an unhealthy plant is discovered, signs appear on its leaves and fruits. Diagnosis of plant disease is hard because of the fact that leaves have distinct symptoms that need to be examined. Even experienced plant pathologists and agronomists have trouble differentiating among various illnesses because of the quantity of adult plants, their extensive prior phytostatic problems, and their inherent ambiguity. This research paper will undergo ML/ deep learning in the field of plant health analysis.

INTRODUCTION

To meet the difficulties confronting farmers, agrochemical firms provide a wide variety of products including those for increased yield, insect resistance, toughness, quality of water, and many other concerns. Marketers should use actual-world circumstances to calculate the effectiveness of their goods, in place of using controlled experiments alone. In single-crop farms, different fields are used and a particular procedure implemented in each. Hybrid seeds are planted in one location while a second location is fertilized, and the process is repeated for as many plots as are necessary. By observing the physical condition of crop in the plot in which the therapy was given, we are able to get a measure of the relative effectiveness of each therapy.

A widely accepted measure of plant growth is the Leaf Area Index (LAI), which has been inured to learn the effects of vegetation (grown as well as wild), climate, and surroundings in hundreds of different research papers. Fertiliser and irrigation efficiencies are critical when it comes to most agronomical and horticultural research. LAI is an essential indication of how much rainfall and sunlight is intercepted; how much energy is converted; how much water is retained; and finally, how much vegetation is formed. Crop making varies depending on the kind of crop, as well as on the phase of the plant's life.

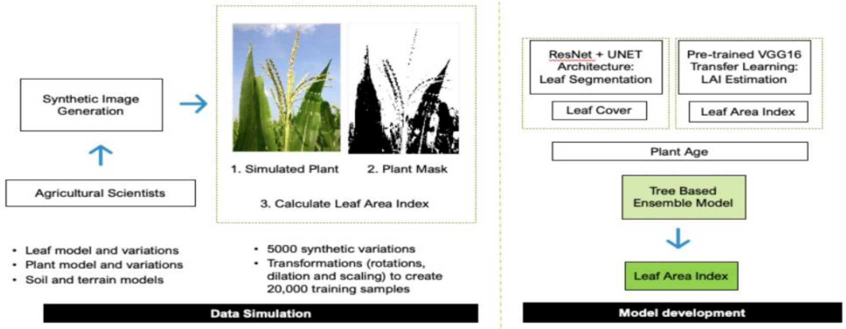
The difficult and time-taking procedure of gathering leaves using traditional LAI measurement takes days or weeks to complete. Every each leaf must be carefully measured to ensure that the length is precise. Because the procedure is laborious and costly, measurements are rare and must be performed on limited controlled regions. Furthermore, in small numbers, the data are inadequate to construct models or train model.

Sophisticated data science methods like drones, computer vision, and sophisticated algorithms are already being used to solve the difficulties facing agrochemical businesses. But nevertheless, such difficulties remain. In crops that develop tall and thin, such as maize, features such as leaf direction, alignment, length, form, and twisting are hard to observe. Additional complications are brought on by non constants including weather, topography, cloud refraction, and occlusion. As already mentioned, variables that influence plant health and treatment outcomes change over time, and frequent monitoring is thus needed. Computer vision and deep learning techniques are maturing, and this is helping scientists in their assessment of LAI. With major agrochemical businesses, Tiger Analytics has created these services. We describe the many methods and difficulties in this post.

In the case of DL, the major difficulties in solving the problem is the scarcity of training data. It would take many months of human leaf measuring and a massive resource investment to train the network adequately. It must be produced (the training data, together with the model source) and the 'real' data (which is rarely acquired and used) is kept for verification.

It is vital to have strong collaboration with botanists and agricultural experts in order to analyze the drone pictures and create leaf profiles. The breadth, twist, and color saturation of each leaf profiles are reproduced for each cross-section. Various random alternatives are implemented to leaf widths, distribution, the leaf area on plants, and plant age, as well as the orientation of development.

It is possible to benefit product quality and avoid economic losses by focusing on plant health evaluation and disease detection. Early diagnosis and species-specific disease categorization are critical to ensure crop production integrity. There have been many observations that have displayed the importance of early identification of plant illnesses since, over time, the species is affected by disease, and its signs emerge on the leaves. If a crop has an illness, and visible symptoms appear on the leaves, they provide a way to recognize and determine the illness. In order to contain the spread of illness, it is difficult to regulate and survey the disease's development. Species of particular fungi or bacteria are often present in spots and blight (lesions). Fungi provide "signs" of illness, such as molds forming and fruiting bodies appearing in the region of dead plant tissue as black spots. Haphazard dark-colored and water-soaked patches



with a distinct border that may have a light-colored ring are occasionally seen when pathogenic bacteria occur during warm conditions on leaves or fruits. The decaying region appears identical to normal tissue, so it is difficult to identify illnesses at first.

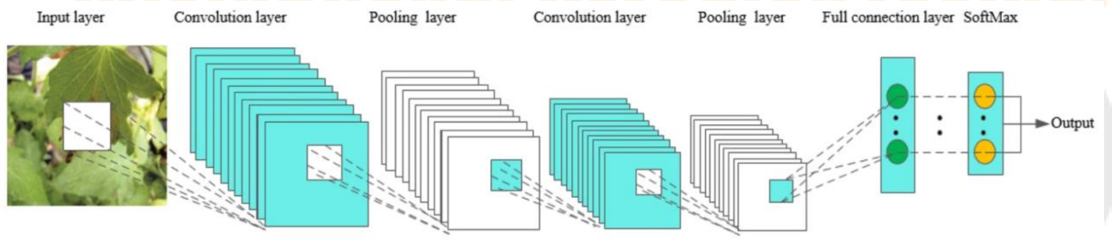
Deep learning theory

Hinton et al. first proposed the idea of Deep Learning (DL) in their article in Science in 2006. Deep learning is the process of utilizing neural networks for data survey and feature learning, where low-level characteristics are retrieved by many hidden units, and then integrate those values to produce abstract high-level features. Existing methods, relying on artificially-designed characteristics, have had their own disadvantages, and deep learning solves them by attracting increasing interest from academics. Computer vision, pattern classification, voice recognition, natural language, and reffering systems are all areas where the algorithm has recently been effectively used.

A manual feature extraction technique are only capable of extracting the feature data, and thus confines the potential of finding deeper and more complicated picture features. Additionally, DL may be used to address this issue. It is able to automatically obtain multi-level image feature material, such as limited features, intermediary characteristics, and high-level semantic, from the real image without supervision. Most conventional plant disease and pest detection algorithms use manual-designed characteristics, which is time-consuming and subject to error, and thus can't be applied mechanically. This statement means that deep learning is not only capable of learning features from huge data sets, but it is able to do it without human modification. It is comprised of many layers, and this provides it with both a high level of learning strength to flexibly represent various characteristics. As a result, it can automatically identify picture content. Due to this, deep learning has the potential to make significant contributions to plant pest and diseases identification picture recognition. To this day, deep learning models such as deep belief network (DBN), deep Boltzmann machine (DBM), stack de-noising auto encoder (SDAE), and deep convolution neural network (DCNN) have produced several well-known models (CNN). By using deep neural network models to provide automated face detection in high-dimensional feature vector, these techniques are more suitable for the problem of picture identification than conventional human design methodologies. The accuracy of deep neural networks is increasing jointly with the quantity of training samples and the computing capacity. This surge in popularity for deep learning is being felt both within the industry and academia, with deep neural network models outperforming conventional models by a considerable margin. A (DCNN) is most often used in recent years in this field.

CNN : - (CONVOLUTION NEUTRAL NETWORK)

A complicated network configuration and the capability to execute convolution operations are ordinary to convolutional neural networks, which are also recognized as CNNs. In Figure 2, the image prediction network model is built from input, convolution, pooling, full link, and output layers. This technique is known as alternating convolution and pooling, and it follows the traditional configuration of a convolution followed by a pooling. In this replica, the convolution and pooling layers exchange a few magnitudes, and then when the neurons of the convolution layer are linked to the neurons of the pooling layer, no full network is established. CNN is one of the most common deep learning models used in industry. CNN's unique structural features allow it to have an edge in picture identification. Meanwhile, CNN's performance in computer vision tasks has served to enhance the rapidly increasing interest in deep learning.



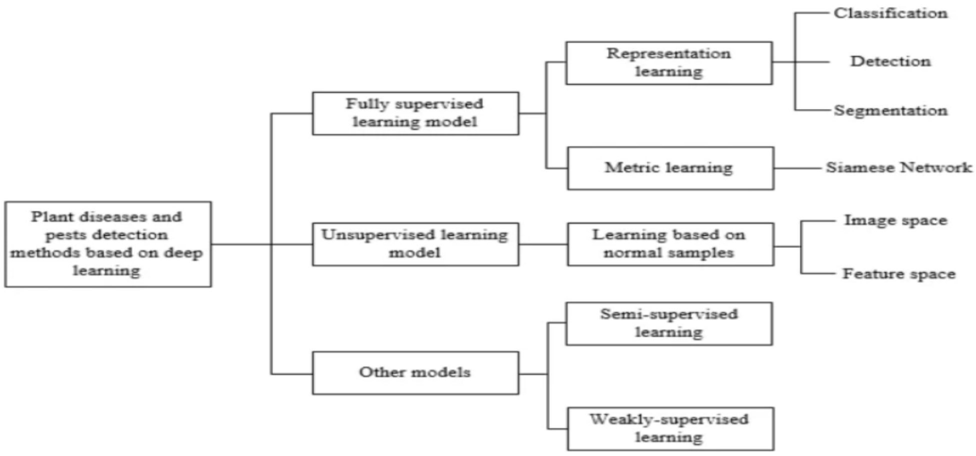
The basic structure of CNN

Convolution core is defined initially in the convolution layer. When used on a local receptive field, the convolution core may be regarded a local receptive field, and the biggest benefit of the convolution neural network is that it works on local receptive fields. Convolution processing occurs on the feature map, which is brought in contact with the convolution core. Extraction of features and pooling happen at the pooling layer after feature extraction is done on the convolution layer. However, there are now three primary ways of pooling, with the most commonly worn one being to utilize the mean, maximum, and random values from the local receptive field. Data enters several convolution and pooling layers, after which they go via a full-connection layer before making it to the top layer of neurons. The softmax technique may be use to recognize values in the full-connection layer, and then those principles are sent to the output layer where they are used to provide results.

TECHNIQUES FOR FINDING PLANT SICKNESS AND PEST OUTBREAKS:

This segment provide a high-level impression of numerous techniques for finding plant disease and pest outbreaks based on deep learning. Even if plant diseases and pests detection techniques based on deep learning align with the computer vision problem, we may still consider them to be a deployment of significant classical networks in the area of agriculture. Figure 3 demonstrates the many network structure possibilities, and how they may be further split based on those structural options. According to the processing features of each kind of techniques, this article is split into many distinct sub-methods, as shown in Fig. 3.

Fig. 3



Framework of plant diseases and pests detection methods based on deep learning

CHALLENGES IN ML/DEEP LEARNING :

To help with data gathering, we now face three major types of challenges: (1) collecting training data, (2) training the model, and (3) ensuring model transferability.

It is critical and difficult to keep algorithm performance optimized when using training data. Research requirements, counting the call for a openly accessible, open-source, joint database on plant stressors at leaf scale, were met by the establishment of the PlantVillage database, which included more than 54 306 pictures of 14 crop species and 26 illnesses. There have previously been numerous studies done on Plant Village data, and more sources of data will be required to build effective models. In addition to the open-source database mentioned above, other open-source databases include a maize NB-lèbre (a common disease) database including 18,222 digital pictures of maize leaves from the field, whether manually taken, placed on a boom, or by unmanned aerial vehicles (UAVs). It's the biggest publicly accessible picture collection annotated for a plant disease. There were about 105 705 NLB lesions annotated by human specialists, making this a huge image set. Over 90% accuracy using 18,000 pictures of agricultural areas in Africa, Latin America, and India, Selvaraj et al. trained a DCNN model for banana sickness and pest classification. By release all of the pictures from their study, the author have permitted the scientific community to contact them. This collection is called the plant disease database (PDDB), and it contains over 2,300 pictures of over 170 plant diseases and other illnesses. Subdividing the pictures to amplify the number of images to 46 513 increased the database size.

CONCLUSION

Plant stress severity phenotyping is a key metric in gauging the risks of crop losses owing to diverse biotic and abiotic stressors. In terms of genetics, better disease-resistant and stress-tolerant genotypes may be identified, and choices about illness management can be assessed. Present methods for measuring stress intensity use the following methods at different scales: Exact count of lesion counts, estimations of the intensity or surface area impacted by a specific stress at covering and field levels, or estimations of the group of species affected by a stress. Image-based disease phenotyping has several benefits, but increasing the speed, accuracy, reliability, and scalability is only possible if ML is used in this process. These concerns include less human error, as well as variability across raters. The purpose is to integrate ML and DL into HTP of plant characteristics in the field for real-time application.

REFERENCES

[1] Stephane Georges Mallat, Understanding Deep Convolutional Networks, Philosophical Transaction of The Royal Society: A mathematical, physical and Engineering Science 374(2065), 2016.

[2] Sharada Prasanna Mohanty, David Hughes, and Marcel Salath, Using Deep Learning for Image-Based Plant Disease Detection, Front. Plant Sci. 7:1419. doi: 10.3389/fpls.2016.01419, 2016.

[3] Amanda Ramcharan, Kelsee Baranowski, Peter McCloskey, Babuali Ahmed, James Legg, and David Hughes, Deep learning for Image-Based Cassava Disease Detection, Front. Plant Sci. 8:1852 doi: 10.3389/fpls.2017.01852, 2017.

[4] Philipp Lottes, Jens Behley, NivedChebrolu, Andres Milioto, CyrillStachniss, Joint Stem Detection and Crop-Weed Classi_cation for Plant-specific Treatment in Precision Farming, IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), 2018.