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Assessment of Stress on Plants Through Neural Networks

Azeem Akhtar
[1]*Quaid e Azam University Islamabad
* Email: Azeem.Akhtar@gmail.com

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Among the many problems that cost growers money, plant stress is a major one. Applications of the traditional methods for identifying stressed plants are limited by the time and effort required to perform the identification. Effective, quick solutions are needed immediately. Changes in precision agriculture using deep learning and big data are being sparked by advancements in cutting-edge sensing and machine learning techniques. In this paper, we surveyed recent advances in deep learning techniques for use in analyzing images for the diagnosis of crop stress. We compiled recent sensor technology and deep learning principles used for plant stress phenotyping. Additionally, we surveyed several deep learning applications/functions that are intertwined with plant stress imaging, such as classification, object detection, and segmentation. Additionally, we summed up the issues plaguing plant phenotyping today and talked about potential future directions for improvement.

Keywords: Neural Network, Artificial Intelligence, Water Stress.

Introduction

A significant drop in crop yield and quality can be attributed to plant stress [1]. Rapid and robust implementation of precision agriculture in crop measurement requires accurate detection and diagnosis of plant stress. Optical imaging methods for plant disease detection are currently the subject of extensive research. Optical imaging is more advanced than traditional methods using visual scoring because it can rapidly and non-contact measure changes in plant physiology due to abiotic or biotic stressors. Digital, fluorescence, thermographic, LIDAR, multispectral, and hyperspectral imaging methods have all been used for crop stress detection [2]. Depicts the most widely used optical sensors for detecting plant stress.

To identify plant diseases, digital imaging sensors gather data in the visible spectrum, acquiring images in red, green, and blue (RGB) color space. These photographs reveal details about the plant's anatomy, including its canopy health, leaf color, leaf texture, leaf size, and leaf shape [3]. Differentiating between a healthy plant and one with symptoms can be difficult, but color and texture differences can help. RGB, LAB, YCBCR, and HSV color spaces are common ones [4]. Texture can also be described in terms of other image characteristics like contrast, homogeneity, dissimilarity, energy, and entropy [5]. Simply put, these pictures have been mined for quantitative diagnosis features that will help distinguish between sick and healthy plants.

Images of infrared radiation between 8 and 12 m, obtained by thermal imaging sensors, are frequently used to make predictions about plant temperatures. The temperature of infected plant tissues changes in response to infection and is correlated with the effects of pathogens. Conversely, it appears that temperature variation has a counter-effect on the rate of transpiration [6]. In other words, as a result of the stress brought on by the infection, the stomata close, and the transpiration rate drops, leading to a rise in leaf temperature. Consequently, thermal imaging sensors could detect infectious diseases based on these changes. The thermal image displays the object's temperature as a false color for each pixel. [7]. Using a fluorescence image sensor and LED or laser light, the photosynthetic electron transform may compare the photosynthesis rates of stressed and healthy leaves. The optimum wavelength under normal conditions is 685 nm. The fluorescent wavelength at which photosystem II emits chlorophyll (PSII). Chlorophyll fluorescence emission patterns may shift in stressed plants, which can be seen in fluorescence imaging [8].

Multispectral imaging sensors are so-called because they capture data from a wide range of wavelengths using optical sensing technologies. Images from the visible to the near-infrared range are typically extracted by multispectral imaging sensors [9]. A decrease in chlorophyll and the ability to absorb visible light is a common response of stressed plants, leading to an increase in visible reflectance. As a result of these alterations, the leaf's NIR reflectance will decrease [10]. Although these sensors can only detect diseases in a limited range of wavelengths and are sometimes unable to assess the severity of infected plants, drones equipped with multispectral image sensors have been routinely employed for remote plant disease detection.

Supervised methods, which use training data to refine an algorithm, have emerged as a favorite among those used for analyzing images. Feature extraction, stress diagnostic classifiers, and shape segmentation are all examples of such techniques [3]. Convolutional neural networks (CNNs) use hundreds of interconnected layers to process images in batches of varying sizes using convolution filters [11]. Despite these early triumphs, advancements in core computing systems have shifted the spotlight to deep convolutional networks. When large datasets are used, deep learning exhibits acceptable performance in the agricultural sector, both in terms of accuracy and efficiency [12] [13]. The combination of deep learning and big data has been suggested as a viable future strategy for plant phenotyping. Disease identification and fruit classification are only two examples of the kinds of field-based jobs where CNNs have proven to excel [14]. The promising results of using deep learning in phenotyping tasks like leaf morphological classification motivate more study in this area. The aims of this work are, in brief:

1. explain how deep learning works in the context of an image-based app for diagnosing crop stress.
2. Conduct research into the difficulties presented by deep learning for crop stress imaging.
3. elucidate potential future avenues that may aid in overcoming obstacles in plant phenotyping tasks.

There are two main differences between MLP and CNN. To begin, the weights of a CNN architecture are shared with a network when the architecture is used to execute convolutions on an input picture. Thus, it is not necessary to train each detector individually if the same object appears in many locations within the same image. This causes exactly as much inconsistency in the network's translation of input images. Therefore, there is less of a need to memorize parameters[15][16].

Two, the pooling layer is the primary differentiator between MLP and CNN. Layers that utilize a permutation invariant function in convolutional neural networks (CNN) supplement their input with pixels from their surrounding area [17] [18]. This could cause some rendering invariance to occur [19]. Depicts a common CNN architecture used for determining strawberry ripeness using hyperspectral images.

Convolutional techniques on picture subsets yield feature connections [20]. Classification, segmentation, object detection, etc. are just some of the many areas where the CNN architecture has been put to use [21].

Related Studies

The five convolutional layers in AlexNet make it one of the simplest pre-trained networks for image classification [22]. Hyperbolic tangent, the most popular choice in CNNs [23], is AlexNet's activation function. Deep pre-trained networks followed, with the 19-layer VGG19 emerging victorious in 2014's ImageNet competition. The 2015 ImageNet competition was won by a network architecture constructed entirely using ResNet components. GoogLeNet is a 22-layer neural network created by a researcher (2016) that makes use of the inception blocks [24]. Using inception blocks has the potential to boost training efficiency while reducing the overall number of parameters [25]. After 2014, there was no further improvement in performance on ImageNet, and attributing this improvement to more complex architectures is erroneous [26]. However, with the deeper networks, plant stress detection is unnecessary, resulting in a smaller data set and less RAM usage. Hence, crop stress images can still be processed using AlexNet and other comparable simple approaches like VGG16.

Analysis of images of crop stress often requires segmentation. Once the CNN has classified an image's pixel, it can present that pixel with patches extracted from surrounding pixels [27]. When this is done, the entire input image can be properly processed by the convolutional network [28].

The widespread development of GPUs may be responsible for the meteoric rise of deep learning applications [29]. The Graphics Processor Unit's (GPU) ability to do computations in parallel is a significant advantage over a standard central processing unit (CPU) (CPU). OpenCL is a framework for writing code that runs on graphics processing units (GPUs), which unifies the various implementations of the GPU's general computing application programming interface (API).processor-graphics processing unit heterogeneous platforms. When compared to the CPU, deep learning runs much more quickly on the GPU [30].

It's worth noting that open-source software libraries contribute to the implementation and spread of deep learning as well. These applications allow users to exert high-level control over computing without having to sweat the efficiency of the underlying code. The most sought-after deals consist of: Caffé was created by UC Berkeley AI Research graduate students and has interfaces in both C++ and Python.

The Google Brain team created TensorFlow, an open-source framework with C++ and Python interfaces. Theano, created by Montreal's MILA lab, is a Python interface for Theano. PyTorch was created by Facebook's AI Research team and offers a C++ and python interface.

The dataset is smaller than those used in computer vision, with each diagnostic serving as a data point (thousands or millions of samples). This is why researchers should prioritize transfer learning for applications like these. Transfer learning makes advantage of already-trained networks to overcome the difficulties of deep network training on large datasets. The extracted features can be easily integrated into preexisting image analysis pipelines, which is another advantage of the former approach over the latter. Still, it's not easy to zero in on the most effective approach [31]. This allowed the identification of multiple illnesses affecting the same leaf. In addition, the authors of this paper used deep learning to identify specific lesions and spots on 14 different plant species. The models in this research were trained with the help of a Google Net CNN that had already been pre-trained. Different needs required categorizing the images into two distinct sets [32]. The first set was designed for image classification, to pinpoint the cause of the symptom being observed, while the second set was dedicated to object detection, to single out diseased tissue in otherwise healthy tissue. The results showed a 12% improvement in precision over using the source photos alone. displays other research that has used deep learning to classify images of crop stress.

The U-Net and the Mask R-CNN are two popular CNN segmentation structures. Biomedical image segmentation was the original application area for the fully convolutional network U-Net (FCN). Hence, a segmentation mapping may be generated immediately by applying U-Net forward on the entire image. Yet, implementing such a network in practice was still challenging. In Table 2, we compile the many ways in which deep learning has been used to the problem of segmenting images of crop stress[33].

R-CNN integrates CNN features with rectangle region recommendations. Typically, R-CNN will use a two-stage detection procedure. First, the system finds potential object regions inside an image, and then it uses those regions to extract CNN features. Next, items from each area are separated into their category. On the other hand, the selective search algorithm is hardcoded, so there is no learning procedure during the preliminary search phase. This may cause some interesting candidate region suggestions to be made [34]. The automatic detection of objects has been a primary focus of computer vision research for some time now, with the hopes of increasing detection accuracy and decreasing manual labor. CNN is used for pixel categorization in deep learning-based object detection, followed by post-processing to obtain object candidates. However, there are still many open questions regarding how to best solve problems such as label imbalance, negative detection, and efficient processing of image pixels, among others [35]. To rephrase, the method offers a workable approach to identifying the specific illness and its location in tomato plants. Recent years have seen significant adoption of the YOLO technique for object detection due to its ability to use a single neural network to both forecast bounding boxes and identify them. The YOLO algorithm first creates an M by M grid out of the image and then extracts m (mM) bounding boxes from within each of those grids. Each box's class probability is calculated by the network [36]. If the bounding boxes' class probabilities are greater than some threshold value, we'd use them to pinpoint the image's subjects. The YOLO network sometimes fails to correctly identify little objects in photos. It provides a quick overview of some alternative object detection uses.

Results and Discussion

Digital, thermal, multispectral, and hyperspectral imagery—collectively referred to as "modality imagery"—have all been used in modal operations, with each modality requiring a different number of spectral channels and sensors (anywhere from three to hundreds). These sensors might employ camera feeds from the outside world to monitor crop dimensions and health. The digital sensors could be used effectively even in daylight. However, the wind will cause the crops to shift locations. In the field, it is still difficult to acquire high-quality images. The crops' physiological properties also evolve as they mature.

Particularly in the case of crops infected by fungi or viruses, which cause biotic stress, these organisms can have significant effects on the plants' physiological responses. Stress in its early stages will be difficult to detect using image analysis because there will be no outward signs of the condition. Additionally, there is a significant lack of datasets, which hinders the practical application of deep learning-assisted image analysis. The PlantVillage dataset provides the majority of the currently available open-source images. However, one major difficulty is the extremely time-consuming task of ground-truth labeling. Amazon SageMaker Ground Truth is a service that facilitates label management and features two distinct components. Annotation consolidation is one option, as it brings together annotated data from multiple users into a single, highly accurate label. The second option is machine learning-based automated data labeling. This method employs AI to automatically assign labels to data samples.

However, this is oversimplifying things, as both of these categories can contain numerous subcategories. For example, almost all of the objects in the healthy group are in pristine condition, with only a tiny fraction displaying signs of early stress. This could result in classifiers that can properly filter out healthy samples but fail to recognize the rare ones. To this end, we intend to annotate every conceivable class in great detail in order to train a multiclass deep learning system. Bayesian optimization has been proposed, but until then, the optimal hyperparameter settings have to be determined empirically.

Conclusion

The majority of the publications we reviewed used 2D imagery, such as digital or grayscale photographs, to depict the clinical stages. Although 2D datasets, such as hyperspectral pictures, are better at detecting early-infected plants, they are not compatible with pre-trained transfer networks that employ deep learning architectures like Alexnet, VGG, and Google Net. Precision disease management requires early detection of plant illness, especially for diseases that cannot be treated with pesticides, and this is why future research should focus on constructing deep neural networks suitable for 3D pictures. While it is possible to outsource parts of the plant stress detection analysis process (such as classification), doing so may not always be the best course of action, especially if additional processing steps (such as segmentation) are required. As far as we can tell, generative adversarial networks (GANs) have been the go-to unsupervised method for identifying plant stress, while variational autoencoders (VAEs) have not been put to much use in this area. While deep learning has been used for other aims in agricultural imaging, such as crop load estimate and harvesting, image reconstruction remains a mostly new area, particularly for LiDAR point cloud data. In plant stress detection, deep learning has demonstrated promising results, which, if applied more broadly, might speed up the emergence of precision agriculture.

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