Deep Learning Plant Health Monitoring (using Sensors)

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***Abstract*—Plant health remain a major aspect to food security in many parts of the world. The yield and quality of plants are greatly influenced by conditions such as plant water stress, diseases and pests. Deep learning has made significant advances in digital image processing in recent years, far superior to traditional approaches. By using sensors and digital image processing, plant health can be monitored and problems can be identified. Researchers are interested in using deep learning technology to identify plant health problems. This paper focuses on identifying plant water stress, diseases and pests and makes a comparison to conventional techniques for doing so. These can be successfully achieved from perspectives of classification networks, detection networks, and segmentation networks, and summarizes both the advantages and disadvantages of each method. Several common data-sets are introduced, and existing studies are compared. Therefore, this study discusses practical challenges in applying deep learning to plant water stress, disease and pest detection. In addition, several suggestions are provided for resolving the challenges and developing new research ideas. Lastly, this study analyzes and predicts the future trends in plant health monitoring using deep learning.**

I. Introduction

Detecting plant diseases and pests is a key area of research in the science of machine vision. It is a system that gathers photos of plants using machine vision equipment and determines whether any pests or illnesses are present [1]. Plant diseases and pests detection tools based on machine vision are currently being used in agriculture and have partially replaced the old-fashioned naked eye identification methods. Traditional image processing algorithms or human feature creation combined with classifiers are frequently employed for machine vision-based methods for detecting plant diseases and pests [2]. To obtain uniform illumination, this method makes use of the different properties of plant diseases and pests to design an imaging scheme and to choose an appropriate light source and shooting angle. While carefully designed imaging schemes can significantly reduce the complexity of classical algorithm design, they can also increase the cost of the application. It is also unrealistic to expect classical algorithms to completely eliminate scene changes from their impact on recognition results under natural conditions. In real complex natural environment, plant diseases and pests detection is faced with many challenges, such as small differences between the lesion area and the background, low contrast, huge variations in scale and type of lesion, and a lot of noise in the lesion image. Additionally, when photos of pests and diseases are taken under natural light, there are a lot of disturbances.
In the recent years, with the successful application of deep learning models represented by convolutional neural networks (CNNs) in many fields of computer vision (CV, computer vision), for example, traffic detection [4], medical image recognition [5], scene text recognition [6], expression recognition [7], face recognition [8].

It is common to use deep learning methods to detect plant diseases and pests in agriculture, and some domestic and foreign companies have developed photo recognition software and We-chat applets that use deep learning to detect plant diseases and pests. Hence, a deep learning-based method for detecting plant diseases and pests is not only important for academic research, but also greatly applicable to the market.

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The content of this study are organised as follows: "Definitions, with subsections plant water stress, plant disease and pest, and plant disease detection" This section gives an overview and definition of plant water stress, Plant diseases and pests detection problem" Comparison with the traditional way of detection“ section introduces and describes some data-sets of plant diseases and pests detection and compares the performance of the existing studies. "Plant water Stress Using Sensors" This section introduces plant water stress and methods of detection. "Machine vision technology" This section explains how machine vision is used in deep learning. "Deep learning theory" "Convolutional neural network" "Deep learning in plant health" This section describes how plant health can be monitored using deep learning, with subsections; Soil moisture estimation, plant water stress detection, classification, detection and segmentation. "Dataset and performance" Dataset distcription and its performance. "Conclusions" section prospects the possible research focus and development direction in the future.

II. Definitions

A. *Plant water stress*

Plant productivity is threatened by water stress, also known as drought stress. In most major crop plants, water availability can reduce yields by more than half. A lack of agricultureal product will in turn create a food security challenge, affecting the nation's economy and threatening farmers' livelihoods. The timely detection and appropriate assessment of plant water stress could minimize the risk of productivity loss.

B. Plant diseases and pests:

Natural disasters such as plant diseases and pests can adversely affect the normal growth of plants and may even result in plant death during the entire plant's growth cycle, In machine vision tasks, plant diseases and pests tend to be concepts from human experience rather than purely mathematical descriptions.

C. Plant diseases and pests detection:

The requirements of plant diseases and pests detection are very general, as compared with the precise classification, detection, and segmentation tasks in computer vision [9]. The requirements can actually be broken down onto three distinct levels: what, where, and how [10]. "What" in the initial step is equivalent to the computer vision classification task. According to Fig. 1, It is labelled with the category to which it belongs. In this stage, the task is classification, which identifies only the image's category. This stage is the rigorous sense of detection in the second stage. "Where" is the location task in computer vision. This stage not only determines what types of diseases and pests are present in the image, but also where they are located. Figure 1 shows a rectangular box marking the plaque area with gray mold. During the third stage, "how" relates to segmentation in computer vision.In Figure 1, gray mold lesions are separated from the background pixel by pixel, which can be used to obtain a series of information, including the size, location, and length of the gray mold lesions, which can be used to evaluate plant diseases and pests at a higher severity level. As a result of feature expression, classification describes an image globally, and then determines whether it contains a particular type of object through classification operations; whereas object detection focuses on local descriptions, that is, identifying what objects exist in which positions in an image. Therefore, apart from feature expression, object structure is the most obvious difference between object detection and object classification. In other words, objectclassification focuses primarily on feature expression, whereas object detection focuses primarily on structure learning. Accordingly, the following text refers collectively to plant diseases and pests detection as a convention, with terminology differing only when different network structures and functions are used.

III. Comparison with traditional plant diseases and pests detection methods

In traditional image classification and recognition methods, only the underlying design features can be extracted, and it is difficult to extract deep and complex image feature information [13]. And Deep learning method solves this problem. Using the original image, it is possible to obtain multi-level features such as low-level features, intermediate features, and high-level semantic features through unsupervised learning. The traditional method of detecting plant diseases and pests is to identify them manually by designing features, and that's hard and depends on experience and luck, and is not capable of learning and extracting features automatically. Deep learning, on the other hand, can automatically identify features from large sets of data without the need to manually manipulate them. Multiple layers are used in the model, which has good autonomous learning capability and flexibility in expressing features, and can classify and recognize images automatically based on their features. In this regard, deep learning can be a very useful tool in helping to detect and identify plant diseases and pests.

IV. Plant water stress using sensors

Plant water stress assessment has been revolutionized by advances in sensing technologies, as illustrated in Figure 2, allowing rapid, automated, and cost-efficient soil-plant ecophysiology assessment and monitoring. As IoT devices have become more popular, environmental sensors have become inexpensive, and these sensors are able to measure agricultural data in real time. Plant water status can also be estimated using a variety of state-of-the-art remote sensing techniques. Plants can suffer from water stress due to a variety of factors. The moisture level of the soil, in particular, correlates with the amount of water that will be available for plants to consume.

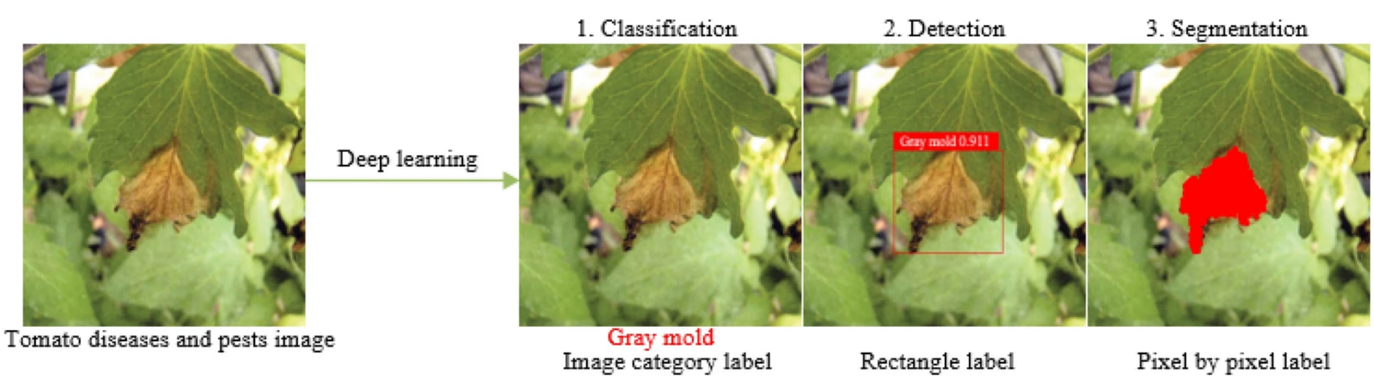

Fig. 1. Definition of plant diseases and pests detection problem

When plants are under water stress, soil moisture is commonly used as an indicator to determine whether they are under water stress. As a result of environmental factors such as temperature, relative humidity, and solar radiation, soil water evaporation and transpiration can reduce the water content of plants. The assessment of plant water stress is thus based on a number of ecological measurements. Recently, the physiological responses of plants to limited water conditions have been used as stress indicators [11]. Plant water stress assessment should be performed directly on the plant, according to Kramer [12], as tissue water condition directly affects plant growth, not soil water level. Nevertheless, most of the methods used to measure plant responses are destructive, time-consuming, and labor-intensive.

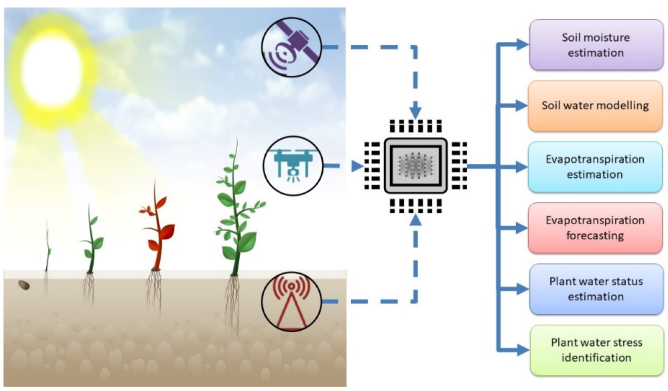

Fig. 2. Techniques for measuring plant water stress based on state-of-the-art sensory measurements.

V. Machine vision technology based on deep learning

As compared to other image recognition methods, deep learning does not require the extraction of specific features, but rather requires iterative learning to identify appropriate features. This method is robust and has higher recognition accuracy, acquiring global and contextual features of images.

VI. Deep learning theory

Deep learning is based on using neural networks to analyze data and learn features.

Multiple hidden layers are used to extract data features, and each hidden layer is considered a perceptron. A perceptron is used to extract low-level features,and then low-level features are combined to obtain abstract high-level features, which reduces the problem of local minimization significantly. In recent years, deep learning has attracted more and more attention due to its ability to overcome the disadvantage of traditional algorithms, which rely on artificially designed features. Currently, it is being used in computer vision to recognize patterns, recognize speech, process natural language, and provide recommendations. Regarding Image recognition with deep neural networks, image recognition can be automated by automatically extracting features from a high-dimensional feature space than with traditional methods. Further, as the number of training samples and computational power increase, deep neural networks' characterization power improves. In the present day, deep learning is sweeping both industry and academia, and deep neural networks outperform traditional models by a significant margin. In section VI, the most popular deep learning framework known as deep convolutional neural network will be further explained.

VII. Convolutional neural network

The CNN, or Convolutional Neural Network, has a complex network structure and is capable of performing convolutions. As shown in Figure , there are five layers in the convolutional neural network model: input layer, convolution layer, pooling layer, full connection layer, and output layer. There is one model in which the convolution layer and the pooling layer alternate several times, but no full connection is necessary between the neurons of the convolution layer and those of the pooling layer. A convolution core is the first component which is defined in the convolution layer. The biggest benefit of the convolution neural network is its local receptive field, which may be viewed as the convolution core. In order to extract part of the feature information from the data information, the convolution core slides on the feature map. After the feature of the convolutional layer has been successfully extracted, the neurons are then placed into the pooling layer so that the feature can be extracted again. At most recently, the well known used methods of pooling consists of calculating the mean, maximum and random details of all values in the local receptive field [20, 21].

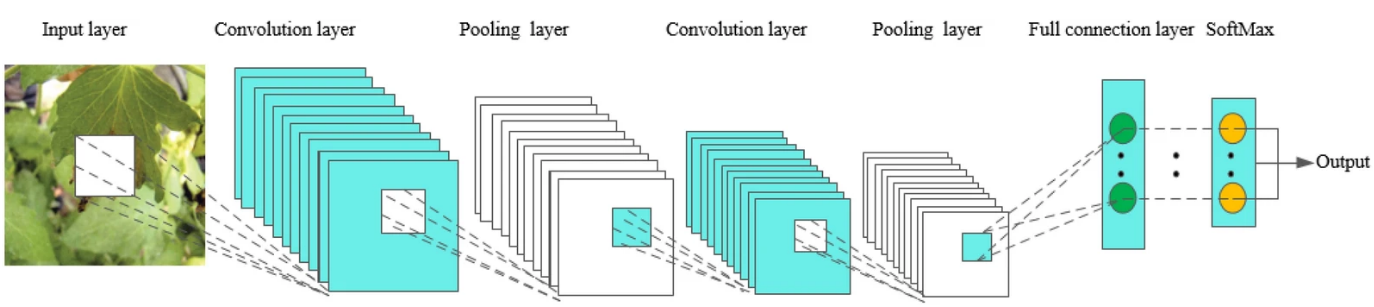

Fig. 3. The fundamental structure of CNN

Afterwards the data enters several convolution layers and pooling layers and then they enter the full-connection layer, after which the neurons in the full-connection layer are fully connected with the neurons in the upper layer. Finally, the data in the full-connection layer can be classified and identified by the softmax method, and these values are then transmitted to the output layer for output results.

For the classification problem described above, we evaluate the applicability of deep convolutional neural networks.Two popular architectures, AlexNet and GoogLeNet, were developed for the ImageNet dataset in the context of the ”Large Scale Visual Recognition Challenge” (ILSVRC). In a similar way to the LeNet-5 architecture from the 1990s, AlexNet follows the same design pattern. In most LeNet-5 architectures, convolution layers are stacked and then one or more fully connected layers are applied.In addition to the convolution layers, all layers of a network typically have non-linear activation units associated with them, such as the normalization layer and the pooling layer. Five convolutional layers make up AlexNet, which is then followed by three fully connected layers and a softMax layer at the bottom. Following each of the first two convolution layers are normalization and pooling layers, while the last convolution layer is followed by just one pooling layer.

VIII. Deep Learning in plant water stress

The main techniques for assessing plant water stress, such as soil moisture estimation, soil water modelling, evapotranspiration estimation, evapotranspiration forecasting, estimation of plant water status, and identification of plant water stress, were used to categorize DL applications into sub-categories as seen in Figure 2. Below is a discussion of the DL methods employed in the examined literature, soil moisture and estimation of plant water status will be discussed below.

A. Soil moisture estimation:

For assessing plant water stress, soil moisture (SM) is an important parameter since it directly relates to water availability. SM measurement has been used in agricultural drought monitoring and irrigation control for many years [26]. SM percentage should not approach the plant-available water limit, which is the lower limit of permanent wilting. With advanced remote sensing techniques, monitoring has become cheaper and more extensive at the same time. From several remote sensing platforms, DL techniques have been used to estimate SM quickly and accurately. DL has been used for aerial image analysis using an unmanned aerial vehicle (UAV) or drone for SM estimation in several studies. A CNN-based regression model was proposed by Sobayo et al. [27] for estimating SM content from aerial thermal images of three different farms. In comparison with plain DNN models, the model was more accurate at predicting SM content. Due to high costs and labor requirements, the technique has a limited application at the scale of captured images. According to the study, CNN generates fewer errors in the prediction of soil moisture dissipation rate from simulated test images than traditional machine learning methods. The CNN method also performed well even when simulated images were noisy.

B. Plant water stress identification:

In plant water stress identification, water stress is detected by distinguishing between water stress and non-water stress in labelled plants. Plant water stress identification systems have been developed over the years using conventional machine learning algorithms, including ANNs [32], adaptive neuro-fuzzy classifiers [33], and gradient of boosting decision trees (GBDT) [34]. In spite of this, the performance of the analysis was limited by the need to extract features from the images and to select conventional machine learning algorithms.

With CNN becoming the standard model for automated feature extraction and transformation, DL’s superiority in image recognition by learning from patterns has been leveraged in plant water stress identification. The first effort to identify plant water stress in maize using pre-trained CNN: Resnet50 and Resnet120 based on three stress treatments—optimal moisture, mild drought, and moderate drought stress—may have been made by An et al. [35]. The models’ results ranged from 91 to 98 percent accuracy, and the quickest training times were around 8 minutes. Resnet50 has the best accuracy in CNN performance, outperforming manually derived features and classification using the traditional GBDT model.

Over the years, many techniques have been developed to describe plant water status (PWS), such as relative water content [40], equivalent water thickness (EWT) and fuel moisture content (FWC) [36]. There are also techniques based on the changes in plant physical characteristics as a result of water content, such as stem diameter variations (SD) [37,38]. Plant conditions related to drought (as water stress index) and irrigation management have been assessed using these parameters [39]. Remote sensing measurements have been used to estimate plant water status non-destructively with different modeling methods to correlate the measurement and ground-measured plant water status, ranging from simple linear regression to machine learning.

IX. Deep Learning in plant diseases and pests detection:

The purpose of this section is to provide a summary overview of deep learning methods for detecting plant diseases and pests. Plant diseases and pests detection methods based on deep learning are fully compatible with computer vision tasks since the goal achieved is completely aligned with the field of agriculture. According to the different network structures shown in Fig 3, the network can be further subdivided into classification networks, detection networks, and segmentation networks. According to the processing features of each type of technique, as shown in Fig. 3, this work is separated into various distinct sub-methods.

A. Classification:

In a natural environment, plant diseases and pests differ in shape, size, texture, color, background, layout, and illumination, which makes recognition difficult. With CNN’s ability to extract features, CNN-based classifiers have become the most commonly used patterns for classifying plant diseases and pests. In general, CNN classification networks start with a cascaded convolution layer, followed by a pooling layer, followed by an average pooling layer and softmax structure. The existing plant diseases and pests classification networks use the modern network structures in computer vision, such as AlexNet [17], GoogleLeNet [18], VGGNet [19], ResNet [20], Inception V4 [21], DenseNets [22], MobileNet [23] and SqueezeNet [33]. Some studies have also designed network structures based on practical problems [24–25]. These networks analyze a test image and return a label that classifies it. The classification network method can be divided into three subcategories based on the different tasks achieved: using the network as a feature extractor, using the network for classification directly, and using the network to locate lesions.

B. Detection:

One of the most fundamental challenges in the field of computer vision is object positioning. Additionally, it is most similar to conventional detection of plant diseases and pests. Its goal is to gather precise location and item categorization information. Deep learning-based object identification techniques are now constantly emerging. Is it possible to replace classification networks with detection networks? It is the task of the detection network to solve the location problem of plant diseases and pests. Meanwhile, the function of a classification network is to determine the type of plant disease and pest. Perceivably, detection network includes the category information, that is, the category information of plant diseases and pests, which needs to be located and needs to be known beforehand, and the corresponding annotation information should be provided in advance to judge the location of plant diseases and pests. To a certain extent, a detection network can answer "what kind of plant diseases and pests are present in what places" when there is strong model differentiation, that is, when the detection network gives accurate results. There are many instances, however, in which it cannot reflect precisely the unique nature of plant diseases and pests categories, but only be able to answer "what kind of plant diseases and pests may be present in what location", which requires the involvement of classification networks. However, the detection network cannot replace the classification network.

C. Segmentation:

Segmentation networks convert the task of detecting plant diseases and pests into semantic and instance segmentation of lesions and normal areas. As well as dividing the lesion area, it obtains the location, category and geometric properties (including length, width, area, outline, center, etc.). Fully Convolutional Networks (FCN) [28] and Mask R-CNN [29] can be used to broadly categorize it. Image semantics segmentation relies on full convolution neural networks (FCNs). Currently, FCN is the foundation of practically all semantic segmentation models. After extracting and coding the features of the input image using convolution, FCN gradually restores the feature image to the size of the input image using deconvolution or up sampling. The plant diseases and pests segmentation techniques may be categorized into standard FCN, U-net, and SegNet [30, 31] based on the variations in FCN network topology.

X. Dataset and performance description

This section first provides a brief overview of the datasets relevant to plant illnesses and pests as well as the deep learning model assessment index. It then compares and analyzes the related deep learning models used in recent years to identify plant diseases and pests.

A. Datasets:

Datasets for the identification of plant diseases and pests serve as the foundation for research. For computer vision tasks such as detecting plant diseases and pests, there is no big and unified dataset compared to that of the ImageNet, PASCALVOC2007/2012, or COCO. The dataset for plant diseases and pests may be obtained by self-gathering, network collection, and usage of open data sets. Unmanned aerial remote sensing, ground camera photography, Internet of Things monitoring video or video recording, aerial photography of unmanned aerial vehicle with camera, hyperspectral imager, near-infrared spectrometer, and other methods are frequently used to self-collect image datasets. Usually, public datasets come from PlantVillage, a well-known public standard library that already exists. Self-gathered datasets on plant diseases and pests in actual natural environments are more useful. Despite the fact that more and more researchers are opening up the images collected in the field, it remains difficult. The objective is to compare them uniformly based on different classes of diseases under different detection objects and scenarios. This section includes links to existing studies as well as datasets related to plant diseases and pests.

B. Performance:

Currently, deep learning is being used to research plant diseases and pests across many crops, including vegetables, fruits, and food crops. In addition to the basic tasks of classifying, detecting, and segmenting, more complex tasks such as judging the extent of infection were also completed. At present, most of the current deep learning-based methods for plant diseases and pests detection are applied to specific datasets, and many of these datasets are not publicly available. It is still impossible to uniformly compare all algorithms based on a single publicly available and comprehensive dataset. Through the continuous development of deep learning, some typical algorithms have gradually improved their performance on different datasets. Although the current studies have achieved incredible breakthroughs, there is still a gap between the complexity of the images of infectious diseases and pests in existing studies and the real-time detection of these diseases and pests using mobile devices. In subsequent studies, larger, more complex, and more realistic datasets will be required to find breakthroughs.

XI. Discussion and Conclusion

Through regression analysis or classification analysis, deep learning is a powerful and versatile tool that can be applied to a wide range of problems. This method is suitable for modeling highly complex plant water stress conditions, plant disease and pests detection. Due to its superior performance compared to conventional ML. We will first of all discuss about plant water stress and then, plant disease and pest detection in this section.

Another advanced method for assessing plant water stress is remote sensing, which provides high spatial, temporal, and spectral resolution. Remote sensing plant water stress assessment using DL is still at an early stage of development, however. For plant water stress assessment, remote sensing thermal and hyperspectral images are extensively used. There are, however, challenges regarding the impact of plant geometric structure and image background on the analysis. It has been proposed to use RGB images for remote sensing estimation of plant water content based on morphological features (Leaf Areas) [41,42] and colour [42] to determine plant physiological responses to water stress. Due to its low cost and ease of use, it is preferred [43]. [44] DL has been successfully applied to segmenting plants from their backgrounds for the purpose of detecting plant water stress.

As a result of the lack of obvious symptoms in plant diseases and pests identification, early diagnosis is difficult, regardless of whether visual observation or computer interpretation is used. The importance of early diagnosis in research and the demand for it are greater, which is conducive to the prevention and control of plant diseases and pests as well as preventing their spread. Images are best captured when there is sufficient sunlight, and taking pictures in cloudy weather will complicate image processing and reduce recognition. Even high-resolution images are difficult to analyze in the early stages of plant diseases and pests. Detection and prediction of diseases and pests must rely on a combination of meteorological data and plant protection data. Research literature shows that few reports have been published on early diagnosis of plant diseases and pests.

With the advent of artificial intelligence, plant diseases and pest detection based on machine vision has moved from classical image processing and machine learning methods to deep learning methods, which solve difficult problems that traditional methods were unable to solve.

XII. Affidavit

I ENEKWA IZUCHUKWU GEORGE herewith declare that I have composed the present paper and work myself and without use of any other than the cited sources and aids. Sentences or parts of sentence quoted literally are marked as such: other references with regard to the statement and scope are indicated by full details of the publications concerned. The paper and work in the same or similar form has not been submitted to any examination body and has not been published. This paper was not yet, even in part, used in another examination or as a course performance.

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