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Review on Various Deep Learning Methods Adopted to Improve the Plant Leaf Disease Classification in Precision Agriculture

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***Abstract*—Precision agriculture achieves substantial development to increase the agricultural yield. Recent studies in perception helps to enhance the precision agriculture by the earlier finding of diseases and infection in plants. In this method, we conduct a review in various Imaging techniques for a crop monitoring method. Here various image processing applications are considered for plants classification, based on the harshness of disease or early detection of stress and classification accuracy. The main focus of this method is the utilization of hyper-spectral imaging and classification of plant health and its ability to classify the disease present in the plant leaves. The study in general considers various deep learning strategies adopted to classify the hyper-spectral images. It further studies the classification accuracy of the deep learning methods like deep Convolutional Neural Network (CNNs), Deep Neural Networks (DNNs) and deep transfer learning. The study further provides the inferences related to the classification of hyper-spectral imaging using deep learning algorithms and its pitfalls like falling at local minima and other related challenges during classification.**

***Index Terms*— Deep Learning Algorithm, Precision Agriculture, Classification, Crop Monitoring.**

I. INTRODUCTION

Plant disease is becoming a major issue in present food safety. Globally, there exist 10-16% losses in world crop harvest every year are due to plant diseases. The demand due to rise in population, increased agricultural productions to 70%. Efficient early disease detection techniques are currently required for controlling plant diseases for food safety and agro-ecosystem sustainability.

The quality of plant crops is seriously affected by the plant diseases and result in serious losses. Life-threatening plant conditions lead to high plant mortality. Suspected plants must be identified prior to their laboratory investigation by their external leaving typical symptoms. These symptoms usually occur in between and later stages of the infection. But it is not reliable that disease is morphologically identified. The detection of the causal agent requires an appropriate method.

The field of detecting plant disease is recently a revolutionized field through advances in biotechnology and

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molecular biology. These laboratory techniques can detect a plant disease with the start of symptoms. These methods are also called molecular markers or techniques for destruction. These methods are tested by using affected leaves as input, followed by interaction with other leaves. Each technique has its own advantages and limitations.

Researchers prefer invasive techniques in terms of its speed and accuracy in detecting a plant disease. Invasive techniques, however, have different reasons for their inconsistency and insensitivity. A study recently found that these methods are not consistent or sensitive, nor are they capable of quantifying viroid levels [13]. Invasive methods [14] have been found to diagnose viral infections effectively, but neither of them was ideal for cost efficiency, speed and accuracy.

II. Mechanism of Deep Learning Classifiers

Deep Learning Classifier (DLC) process the raw hyper-spectral image. It does not need preprocessing, segmentation and extraction of features. As a consequence, DLC is more accurate in its classification as it eliminates the errors associated with incorrect vector or imprecise segmentation. DLC approaches have changed the focus of research on the achievement of optimal results from the traditional imaging methods for feature design and network architecture. DLC networks typically consist of multiple hidden layers, which therefore means more computational operations in comparison to ML-based approaches.

Leaves form the input vector and object classes as the output vector for the machine classifier. Deep learning is an improved version of artificial neural networks (ANN) and have more layers than ANN. The input data of the previous layer are regarded as representational learning, because each layer transforms it into another representation at a higher and slightly more abstract level. This enables the model to learn locally and interconnect the entire data in a hierarchical structure.

The non-linear function results in the data transformation and optimal representation of data at each layer in a deep learning model. Features extracted from the first hyper-spectral image layer usually identify the occurrence or absence of edges in the specific alignment and their position in the hyper-spectral image. In the second layer, patterns are detected through edge positioning and minor differentials are ignored, while in the third layer, these patterns are assigned to larger combinations that match the pieces of similar objects. The successive layers are able to identify objects through these combinations.

III. CNN

At present, deep learning in CNNs has been getting increased response. The most active research area in hyper-spectral data analysis is unsupervised classification. Deep learning in NNs has gained a lot of prominence in recent years. The most active field of research in hyper-spectral data analyze is the unattended classification. CNN is an uncontrolled deep learning design in the hyper-spectral image domain that learns the filters. The difference between CNN and conventional NNs is that the retinal fields of the visionary system inspire CNN. CNN is an integration between biological vision and the neural system.

Lowe, A., et al. (2017) developed a complex CNN architecture, which requires longer neural network formation. Nevertheless, the rating is remarkably accurate and the recognition rate of objects is very high [1].

Sladojevic, S., et al. (2016) developed a plant disease recognition model based on CNN Classification. A wide variety of hyper-spectral images, including powdery mildew, rust, leaves, wilt, mites and downey mildew have been downloaded online. The overall detection precision of this model was 96.3%.[2].

Langford, Z. L., et al. (2017) developed an Arctic Vegetation Map that includes hyper-spectral and terrain data sets with a multi-sensor data fusion approach. They found that the CNN model has the highest data content in hyper-spectral datasets. Spectral signatures produced from hyper-spectral data have played an important role in vegetation predictability. From the perspective of multi-sensor data, it is believed that vegetation maps make it possible to remotely detect plant diseases spread over broad areas [3].

In this study of CNN, Lee, S. H. et al. (2020) examined the necessity of pre-trained model for plant identification than object rejection. It is found that the traits learned differ in the approach taken and do not necessarily concentrate on the affected portion of the disease through visualization techniques [4].

Zhong, Y., & Zhao, M. (2020) developed a three-layered regression method, which consists of a multi-label classification process. This primarily uses a loss function, which is developed for DenseNet-121 to identify the diseases that occur in apple leaf. For data modeling and method assessment, the apple leaf hyper-spectral image data set includes 2462 images with six apple leaf diseases. Their precision was better than traditional multi-classification methods with a cross-entropy loss function of 92.29% [5].

Karlekar, A., & Seal, A. (2020) designed a two-module approach [6]. The first module extracts the entire hyper-spectral image from the leaf part with the proper removal of complex backgrounds. The second module provides the soybeans plant recognition soybean leaf images with SoyNet, a deep learning convolution neural network (CNN). The results show that nine state-of-the-art methods are superior to this method.

Sharma, P., et al. (2019) used segmented hyper-spectral image data for training CNN models. When tested with independent data previously unseen in the models even with ten classes of disease, the S-CNN model trained with segmented hyper-spectral images. The applicability of automated methods for the early detection of diseases is brought closer to non-experts through this work [7].

Mishra, S., et al. (2020) presented a method on recognizing maize leaf disease is developed using a deep CNN in real time [8]. DNN performance is improved through the tuning and adjustment of hyper-parameters on the GPU-system. In addition, it optimizes the number of parameters to be suitable for inferences in real time. Intel Movidius Neural Computing Stick consisting of specific CNN hardware blocks was used for the pre-trained CNN model on raspberry pi 3. The deep learning model, which demonstrates the feasibility of this method, achieves an accuracy of 88.46% when maize leaf diseases are recognized.

Hu, G., et al. (2019) suggested an enhanced deep CNN method for identification of tea leaf disease. In enhanced deep CNN of a CIFAR10-fast model, a mixed function extraction module is added, which enables the hyper-spectral image features of various Tea Leaf disorder to be automatically extracted. An accuracy of 92.5% is obtained compared to conventional deep learning methods. The number of parameters used in the improved model is significantly lower than the number of deep network model VGG16 and AlexNet[9].

Further, Darwish, A., et al. (2020) developed a set of two pretrained CNNs namely VGG16 and VGG19. CNNs are used to solve the practical glitches associated with the problem of classification of plant disease because of their capacity to overcome. An exponential decreasing learning rate schema is used to prevent CNNs from falling into local levels and training efficiently. A non-evolutionary method is developed on IntroductionV3 and Xception are pretrained CNN models with the chosen hyper-parameters [10].

Picon, A., et al. (2019) presented a challenging dataset of 100,000 images from a cellular phone in wild field conditions. This data set contains nearly equal distribution of 17 disease stages and five plants with multiple diseases in the same panel. When using existing DNN methods in order to validate two hypothesized approaches, the smaller crop model specifications are achieved with a balanced precision and precision when a single multi-crop model was created. Three different CNN architecture are incorporated with contextual metadata which includes crop information, into the hyper-spectral image-based CNN are proposed [11].

Thenmozhi, K., & Reddy, U. S. (2019) developed CNN to perform the automatic extract of hyper-spectral image classification applications and learns complex high-level features. They developed an efficient deep CNN model for classifying insect species into three public data sets. The results of the model were validated with previously trained deep learning architecture for the insect classification, such as AlexNet, ResNet, GoogLeNet or VGGNet[12].

Sambasivam, G., & Opiyo, G. D. (2020) developed a CNN model was developed with high precision due to two reasons: a small dataset with a strongly biased imbalance. In machine learning methods, class inequalities are problematic and exist in many areas. Interestingly, class imbalance has received little attention in multi-class hyper-spectral image datasets. The focus of this method was on techniques to achieve an accuracy of more than 93% with grade weight, SMOTE, and focus loss with deep CNN scrap. The objective was to combat high-class equilibrium, so the model could accurately predict classes that are underrepresented]13].

Park, K., et al. (2018) proposed a minimal redundancy and maximum pertinence (mRMR) to select essential raw bands directly from hyper-spectral pics. Furthermore, a DNN is proposed for the classification of reduced dimensional hyper-spectral data consisting of a CNN with a fully interconnected network (FCN). Better diagnosis is possible with optimal reduction of complexity in hyper-spectral images [14].

Saleem, G., et al. (2019) presented a handcrafted visual leaf features, their extraction techniques and classification methods. In order to recognize plant types, five-step algorithm is presented. The best KNN for the final results reveals that, when tested on 'Flavia' datasets, which provides an accuracy and retrieval rate of 97.6% and 98.8% respectively. AlexNet is also compared to a man-made functionality-based approach for the classification of data sets, and it is discovered that the latter exceeds the former with smaller dataset [15].

Ma, J., et al. (2018) proposed DCNN for cucumber diseases symptomatic identification. The symptom cucumber leaf hyper-spectral images are divided into images taken under field conditions. DCNN achieved good accuracy on an enlarged dataset containing 14,208 symptom images of 93.4%[16].

The three-channel CNN model developed in Zhang, S., et al. (2019) is a combination of three-color components to detect the disease in vegetable leaf[17]. In each model one of the three-color components of the RGB diseased leaf hyper-spectral image is supplied to each channel and the convolutional feature is acquired at each CNN and transmitted for the vector functionality recognition in the convolutional and pooling layer. Finally, a SoftMax layer uses the vector to categorize the input images into classes.
Zeng, W., & Li, M. (2020) proposed Self-Attention CNN to identify crop diseases on optimal extraction of effective traits of crop disease spots. Our SACNN contains a basic network and a focus network: the core network is to extract the global hyper-spectral image characteristics and the attention network to acquisition of the local characteristics of the lesion area. The accuracy of SACNN on MK-D2 override the 2.9% with self-CNN. The proposed algorithm is able to focus on the main areas of the hyper-spectral image and improved the recognition accuracy [18].
Khamparia, A., et al. (2019) intended to work through deep CNN learning architecture to develop disease identification methods in several seasonal crops. A database with 600 hyper-spectral images, i.e. 200 hyper-spectral images of individual crop variants marked with 10 types of plant diseases, was preferred in this study. There are two classes in each variety, i.e. healthy and rusty plants. They are different. CNNs are so trained that diseases from infected crop varieties are detected[19].
Singh, U. P., et al. (2019) developed an adequate and effective diagnostic method for the fungal disease anthracnose. A multi-layer CNN (MCNN) model is used to classify mango leaves that have been infected. It is validated on 1070 hyper-spectral images from mango tree leaves in real-time[20].
Zhang, X., et al. (2018) developed CNN over large data sets that contain a variety of conditions are required to function properly. In view of many challenges involved in building a suitable hyper-spectral image database, this is an important limitation. In this context, we examine how the size and variation of the datasets affects the efficacy of the deep learning techniques used in pathological plants. This study was based on a 12-plant species hyper-spectral image database, each of which had different sample number, number of diseases and various features [21].
Barbedo, J. G. A. (2018) developed GoogLeNet and Cifar10 deep learning models with less parameters of improved models than those of VGG and AlexNet structures. The Google Net model has a high-1 average identifying accuracy of 98.9%, and the Cifar10 model achieves an average accuracy of 98.8%. These results are observed on eight kinds of deceased maize-leaves. Various improved methods are suggested to improve the accuracy of maize leaf disease and reduce the iteration of convergence. These algorithms can effectively enhance model training and recognition efficiency.

IV. DNN

Rangarajan, A. K., et al. (2018) developed a DNN learning model for the classification of tomato crops. In order to address the problem, a fast and reliable method of non-destruction will benefit farmers in the early diagnosis of diseases. This study gives input to two in-depth learning designs namely AlexNet and VGG16 network, tomato leaves hyper-spectral images obtained from PlantVillage dataset. In classification, accuracy and execution time, the roles of numbers of images and hyper-parameters are analyzed: mini-batch size, weight and distortion learning rate [22].
Ramesh, S., & Vydeki, D. (2019) developed an optimized DNN in paddy leaf diseases using Jaya algorithm. The hyper-spectral images of rice plant leaves are collected directly for the image acquisition. In pre-processing, RGB images are converted into HSV images for background removal. The binary images are extracted based on the hue and saturation to divide the healthy and diseased part. Disease classification is performed with the Jaya Optimization Algorithm, using Optimized DNN[26[.
In order to introduce an expert system that helps coffee producers in the initial phase of their disease diagnosis, Sorte, L. X. B., et al. (2019) used computational methods to recognize the coffee leaf diseases[23]. In this work, two texture characteristics are considered: statistical and local binary characteristics. The most successful Kappa coefficient was 0.970, with a sensitivity of 0.980.

V. Deep Transfer Learning (DTL)

In order to identify plant leaf diseases, Chen, J., et al. (2020) studied transfer learning from the deep CNN, considering the pre-trained model of the standard massive datasets[24]. Their approach selects the VGGNet pre-trained on the ImageNet and Inception module. ImageNET instead of starting training at all costs on randomly

initializing the weights. This approach represents a significant improvement in performance compared to other cutting-edge methods; the validation accuracy of the public information set is no less than 91.83%.
Applied to different data sets, Kaya, A., et al. (2019) developed DNNs. However, DNNs are frequently applied in isolation and no effort was made to reuse it and transmit information on various DNN applications. Machine learning involves using the results of multiple DNN applications in transferring learning. The test shows that transfer learning can bring important advantages to automatic plant identification[25].

VI. Future Recommendations

Deep learning is one among the advanced technology for big data analysis. There are many layers in a deep learning model. Nerve cells of each layer are closely connected to the data characteristics, which allows for more complex information. Deep learning models learn the input data characteristics through a hierarchically structured neuron network. Recent literature on the assessment of deep learning models with digital imaging, hyper-spectral image analysis and hyper-spectral imagery for the detection of the disease has been presented.
Deep learning is believed to be a hyper-spectral remote sensing future. CNN in an image-domain most popular deep model. For the purpose of classification of plant diseases, CNN can be used for hyper-spectral images. Today the most promising areas of deep learning are multimedia and computer vision and natural language processing. The cloud computing architecture and the future scope of the NN-hyper-spectral approach are identified. A large volume of hyper-spectral images based on a cloud computing architecture can be clustered with a distributed frame.

VII. Conclusions

In this method, we found a improvements over plant leaf detection using the CNN performance over other models. High performance shows the capacity of deep learning techniques to identify immediate crop diseases through the various extraction models. DNNs are previously used only for data mining, but their diverse applications with hyper-spectral data now show a significant promise in the detection of disease. Researchers have often faced new challenges in DNN applications, as in many other technologies. For example, three different categories of manifestation diseases are detected. For the accurate rating, the best trainer sets are required for prerequisite, symptomatic and asymptomatic diseases of a single plant. The DNNs demonstrated unbeatable ability to adapt hyper-spectral data to new challenges in disease detection. DNNs have been used for a number of purposes, e.g. data dimensionality reduction, pixel values of images or spectra training as input sets, generalization of input sets, and classification.

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