Literature Survey on Plant Disease Recognition Based on Loss Reweighting Approach

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Abstract- *In this paper systematically investigate the problem of visual plant disease recognition for plant disease diagnosis. To facilitate the plant disease recognition research, construct a new large-scale plant disease dataset with 271 plant disease categories and 220,592 images. Based on this dataset, tackle plant disease recognition via reweighting both visual regions and loss to emphasize diseased parts. First compute the weights of all the divided patches from each image based on the cluster distribution of these patches to indicate the discriminative level of each patch. Then allocate the weight to each loss for each patch-label pair during weakly-supervised training to enable discriminative disease part learning. Finally extract patch features from the network trained with loss reweighting, and utilize the LSTM network to encode the weighed patch feature sequence into a comprehensive feature representation. Extensive evaluations on this dataset and another public dataset demonstrate the advantage of the proposed method.*

Keywords- Plant disease, loss reweighting, LSTM network

I. INTRODUCTION

Rapid and accurate diagnosis of crop diseases is significant to develop the treatment technique while substantially improving agricultural production and ensuring food safety [1].Plant disease diagnosis through optical observation of the symptoms on plant leaves, incorporates a significantly high degree of complexity [2].Plant diseases can cause great damages to agriculture crops by significantly decreasing production. Early blight is a typical example of disease that can severely decrease production [3].The plant diseases are a major thread to losses of modern agricultural production. Plant disease severity is an important parameter to measure disease level and thus can be used to predict yield and recommend treatment. The rapid, accurate diagnosis of disease severity will help to reduce yield losses [4].In remote sensing and earth observation, land cover classification (LCC) is one of the key challenges due to its wide ranging applicability [5].The problem of efficient plant disease protection is closely related to the problems of sustainable agriculture and climate change [6] .They are combined with different methods of image preprocessing in favour of better feature extraction.As previously set out, we aim to model the sequential change of crop phenology during the growth season to assist further land cover classification. Inspired by recent advances in machine learning and computer vision, we propose to employ long short-term memory (LSTM)networks to learn vegetation grammar patterns based on sequential observations.

II. METHODOLOGIES

J. Wang, L. Chen [2018] This paper proposes the latest breakthrough in the field of computer vision, deep convolutional neural network (CNN) is very promising for the classification of crop diseases. However, the common limitation applying the algorithm is reliance on a large amount of training data. In some cases, obtaining and labeling a large dataset might be difficult. We solve this problem both from the network size and the training mechanism. In this paper, using 2430 images from the natural environment, which contain 2 crop species and 8 diseases, 6 kinds of CNN with different depths are trained to investigate appropriate structure. In order to address the over fitting problem caused by our smallscale dataset, we systemically analyze the performances of training from scratch and using transfer learning. In case of transfer learning, we first train Plant Village dataset to get a pre-trained model, and then retrain our dataset based on this model to adjust parameters. The CNN with 5 convolutional layers achieves an accuracy of 90.84% by using transfer learning. Experimental results demonstrate that the combination of CNN and transfer learning is effective for crop disease images classification with small-scale dataset.

Fig.1. Sample images from Plant Village dataset

Fig. 2. Example each from every crop disease. (1) Cucumber target spot (2) Cucumber powdery mildew
(3) Cucumber downy mildew (4) Rice bacterial blight (5) Rice falsesmut (6) Rice blast (7) Rice flax spot (8) Rice sheath blight

The CNN with 5 convolutional layers can reach 90.84% classification result by using the training mechanism of transfer learning, demonstrating that the combination of CNN and transfer learning strategy is effective for classification of various crop diseases.

K. P. Ferentinos [2018] This paper describes the, convolutional neural network models were developed to perform plant disease detection and diagnosis using simple leaves images of healthy and diseased plants, through deep learning methodologies. Training of the models was performed with the use of an open database of 87,848 images, containing 25 different plants in a set of 58 distinct classes of [plant, disease] combinations, including healthy plants. Several model architectures were trained, with the best performance reaching a 99.53% success rate in identifying the corresponding [plant, disease] combination (or healthy plant). The significantly high success rate makes the model a very useful advisory or early warning tool, and an approach that could be further expanded to support an integrated plant disease identification system to operate in real cultivation conditions.

Fig. 3. Examples of correct classifications of various images of the testing dataset

The most successful model architecture, a VGG convolutional neural network, achieved a success rate of 99.53% (top-1 error of 0.47%) in the classification of 17,548 previously unseen by the model plant leaves images (testing set). Based on that high level of performance, it becomes evident that convolutional neural networks are highly suitable for the automated detection and diagnosis of plant diseases through the analysis of simple leaves images.

M. Brahimi [2018] Many researchers have been inspired by the success of deep learning in computer vision to improve the performance of detection systems for plant diseases. Unfortunately, most of these studies did not leverage recent deep architectures and were based essentially on AlexNet, GoogleNet or similar architectures. Moreover, the research did not take advantage of deep learning visualization methods which qualifies these deep classifiers as black boxes as they are not transparent. In this chapter, we have tested multiple state-of-the-art Convolutional Neural Network (CNN) architectures using three learning strategies on a public dataset for plant diseases classification. These new architectures outperform the state-ofthe- art results of plant diseases classification with an accuracy reaching **99.76%**. Furthermore, we have proposed the use of saliency maps as a visualisation method.

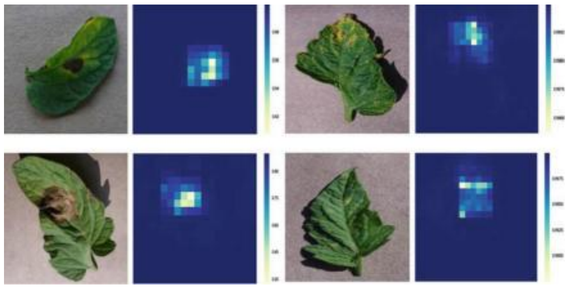

Fig.4. Occlusion experiments in plant diseases classification. The red squares drawn in the leaves images represent the most active occluded parts in the heat map

The results of this evaluation show clearly that we can improve the accuracy using a new CNN architecture such as inceptionV3 which achieved an accuracy of 99.76%.

G. Wang, Y. Sun [2017] Automatic and accurate estimation of disease severity is essential for food security, disease management, and yield loss prediction. Deep learning, the latest breakthrough in computer vision, is promising for fine-grained disease severity classification, as the method avoids the laborintensive feature engineering and threshold-based segmentation. Using the apple black rot images in the Plant Village dataset, which are further annotated by botanists with four severity stages as ground truth, a series of deep convolutional neural networks are trained to diagnose the severity of the disease. The performances of shallow networks trained from scratch and deep models fine-tuned by transfer learning are evaluated systemically in this paper. The best model is the deep VGG16model trained with transfer learning, which yields an overall accuracy of 90.4% on the hold-out test set. The proposed deep learning model may have great potential in disease control for modern agriculture.

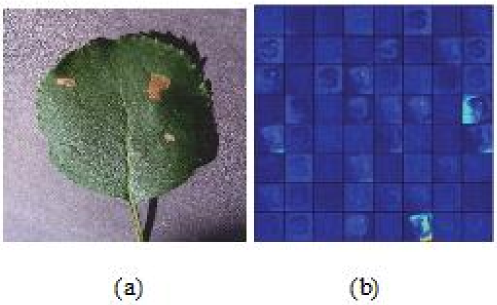

Figure 5: Visualization of activations for an input image in the first convolutional layer of the pretrained VGG16 model: (a) original image; (b) the first convolutional layer output.

The fine-tuned VGG16 model performs best, achieving an accuracy of 90.4% on the test set, demonstrating that deep learning is the new promising technology for fully automatic plant disease severity classification.

M. RuBwurm [2017] Land-cover classification (LCC) is one of the central problems in earth observation and was extensively investigated over recent decades. In many cases, existing approaches concentrate on single-time and multi- or hyper-spectral reflectance measurements observed by space borne and airborne sensors. However, land-cover classes, such as crops, change their reflective characteristics over time, thus complicating a classification at one particular observation time. Opposed to that, the secharacteristics change in a systematic and predictive manner, which should be utilized in a multi-temporal approach. We employ long short-term memory (LSTM) networks to extract temporal characteristics from a sequence of SENTINEL 2A observations. We compared the performance of LSTM networks with other architectures and a support vector machine (SVM) baseline and show the effectiveness of dynamic temporal feature extraction. For our experiments, a large study area together with rich ground truth annotations provided by public authorities was used for training and evaluation. Our rather straightforward LSTM variant achieved stateof-the art classification performance, thus opening promising potential for further research.

Figure 6. Sequence of observations along the growth season 2016. Observed fields change in a systematic and predictive manner based on crop phenology, which can be utilized for classification.

Overall, as the performed experiments show, the temporal LSTM and RNN networks performed better than the non-temporal CNN and SVM models specifically on classes which inherit temporal characteristics, such as crops. Hence, we believe to have demonstrated that LSTM networks can utilize the temporal characteristics in the context of earth observation at the example of crop classes.

S. Sladojevic [2016] The latest generation of convolutional neural networks (CNNs) has achieved impressive results in the field of image classification. This paper is concerned with a new approach to the development of plant disease recognition model, based on leaf image classification, by the use of deep convolutional networks .Novel way of training and the methodology used facilitate a quick and easy system implementation in practice. The developed model is able to recognize 13 different types of plant diseases out of healthy leaves, with the ability to distinguish plant leaves from their surroundings. According to our knowledge, this method for plant disease recognition has been proposed for the first time. All essential steps required for implementing this disease recognition model are fully described throughout the paper, starting from gathering images in order to create a database, assessed by agricultural experts. Caffe, a deep learning framework developed by Berkley Vision and Learning Centre, was used to perform the deep CNN training. The experimental results on the developed model achieved precision between 91% and 98%, for separate class tests, on average 96.3%.

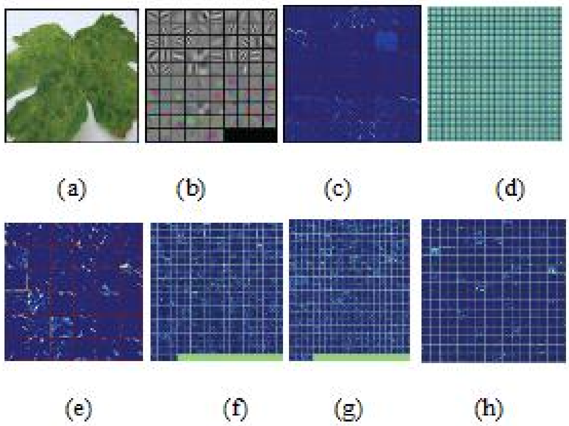

Figure 7: Visualization of features in trained classification model: (a) original image; (b) the first layer filters, Conv1; (c) the first layer output, Conv1 rectified responses of the filters, first 36 only; (d) the second layer filters, Conv2; (e) the second layer output, Conv2 (rectified, only the first 36 of 256 channels); (f) the third layer output, Conv3 (rectified, all 384 channels); (g) the fourth layer output, Conv4 (rectified, all 384 channels); (h) the fifth layer output, Conv5 (rectified, all 256 channels).

New plant disease image database was created, containing more than 3,000 original images taken from the available Internet sources and extended to more than 30,000 using appropriate transformations. The experimental results achieved precision between 91% and 98%, for separate class tests. The final overall accuracy of the trained model was 96.3%. Fine-tuning has not shown significant changes in the overall accuracy, but augmentation process had greater influence to achieve respectable results.

III. RESULT AND DISCUSSION

In this work, we concentrated on the effects of temporal characteristics on the classification performance. Following this reasoning, we decided to fix the receptive field of our networks to 3 ×3 px.
Hence, we effectively restrict the end-to-end learning scheme in terms of spatial extent.

IV. CONCLUSION

In this survey paper, various plant disease and its subtypes are identified. Results showed that the proposed method performed better than the conventional methods. The scheme proposed in this paper effectively reduced the influences of uneven illumination and clutter background to the segmentation of disease images captured under field conditions.

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