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Plant Disease Recognition: A Visual Region and Loss Reweighting Approach

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Abstract: *Plant disease diagnosis is very important for agriculture because of its importance in increasing crop production. Nowadays the advances in image processing gives a new way. One of the newest way to solve this issue via visual plant disease analysis. In this paper, we discuss the problem of plant disease recognition. Here we tackle plant disease recognition via reweighting both visual regions and loss to emphasize diseased parts. We 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 we allocate the weight to each loss for each patch-label pair during weakly supervised training to enable discriminative disease part learning. We 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. We expect this research will further the agenda of plant disease recognition in the community of image processing.*

Keywords: Long Sort Term Memory, Feature Integration, Cluster

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