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Crop Leaf Disease Detection and Classification Using Deep Learning Algorithm

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Abstract: *Plant disease identification is vital for agriculture because it is essential for enhancing crop yields. Visual plant disease analysis is a novel technique to handle this problem because to recent developments in image processing. There are, however, few works in this field, let alone comprehensive studies. We investigate the challenge of visual plant disease detection for plant disease diagnosis in this research. Plant disease photos, in comparison to other types of photographs, tend to have randomly dispersed lesions, varied symptoms, and complex backgrounds, making discriminative information difficult to capture. We created a new large-scale plant disease dataset containing 271 plant disease categories and 220,592 photos to aid plant disease recognition studies. We approach plant disease recognition using this dataset to emphasise sick portions by reweighting both visual regions and loss to determine the discriminative level of each patch, we first compute the weights of all the divided patches from each image based on the cluster distribution of these patches. Then, during weakly-supervised training, we assign weight to each loss for each patch-label pair to enable discriminative disease component learning. Finally, we use the LSTM network to encode the weighed patch feature sequence into a comprehensive feature representation, extracting patch features from the network trained with loss reweighting. Extensive tests on this and another publicly available datasets show that the proposed strategy is superior. We anticipate that our study will advance the plant disease recognition agenda in the image processing community.*

Keywords: Convolutional neural network (CNN), Active Contour Method, Deep learning.

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